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Article

AUTOMOTIVE SYSTEM RELIABILITY AND TECHNOLOGICAL CONVERGENCE: A REVIEW OF SMART POWERTRAIN AND MECHATRONIC DIAGNOSTICS

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ABSTRACT
The evolution of automotive systems has accelerated with the integration of intelligent electronics, embedded sensors, and AI-driven software, resulting in increasingly complex vehicles that demand advanced diagnostic and reliability frameworks. This systematic review explores the convergence of technologies that underpin smart diagnostics, focusing on powertrain systems, mechatronic diagnostics, artificial intelligence, digital platforms, and cybersecurity. Guided by the PRISMA 2020 methodology, a total of 112 peer-reviewed articles were rigorously analyzed to identify key advancements, application trends, and emerging challenges in automotive fault diagnostics and system reliability. The findings reveal a paradigm shift from traditional, reactive maintenance approaches to predictive and condition-based strategies enabled by real-time sensor monitoring, machine learning algorithms, and cloud-edge computing architectures. Notably, the implementation of AI techniques—such as convolutional neural networks, support vector machines, and unsupervised learning models—has enabled earlier and more accurate fault classification across critical systems, including powertrains, batteries, and thermal subsystems. The review also highlights the growing adoption of digital twin technologies, which allow virtual modeling of vehicle components for predictive maintenance, system optimization, and remote diagnostics without physical testing. Additionally, the incorporation of cybersecurity frameworks, particularly SAE J3061 and ISO/SAE 21434, is shown to be essential in protecting diagnostic systems against evolving digital threats in connected vehicle environments. Cloud-based and edge-based diagnostic platforms emerged as scalable solutions for managing real-time fault data, supporting over-the-air updates, and ensuring rapid decision-making in distributed vehicle networks. A recurring challenge identified across the literature is the widening skill gap in diagnostics engineering, particularly in the application of AI and systems integration, which hampers effective technology adoption in industry settings. Furthermore, the review underscores the importance of standards compliance and system interoperability to ensure diagnostics consistency across multi-vendor environments. By synthesizing insights from 112 high-impact studies across multiple disciplines, this review offers a comprehensive assessment of current capabilities, limitations, and future directions in smart diagnostics and automotive reliability management. It serves as a critical resource for researchers, engineers, and industry leaders aiming to optimize vehicle performance, safety, and maintainability through intelligent diagnostics technologies.

KEYWORDS
Automotive Reliability; Smart Powertrain Systems; Mechatronic Diagnostics; Technological Convergence; Vehicle Health Monitoring;

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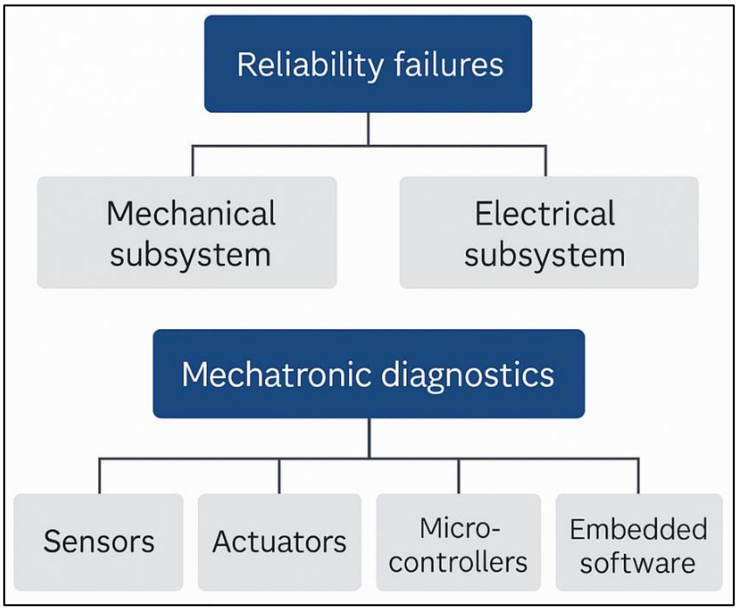
INTRODUCTION

Automotive system reliability is broadly defined as the ability of a vehicle's components and systems to perform their intended functions under specified conditions for a designated period without failure (Gumiel, 2024). This concept is a cornerstone in modern automotive engineering, directly influencing vehicle safety, operational efficiency, and lifecycle cost. In technical terms, reliability encompasses measures such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and Failure Mode and Effects Analysis (FMEA) (Kang et al., 2024). Complementary to reliability is the field of mechatronics, an interdisciplinary domain that integrates mechanical systems, electronics, control engineering, and computer science (Jiang et al., 2018). Mechatronic systems are pervasive in modern vehicles—spanning from Anti-lock Braking Systems (ABS) to Electronic Stability Control (ESC)—and rely heavily on sensors, actuators, microcontrollers, and embedded software (Quintana et al., 2021). Mechatronic diagnostics refer to the methodologies and tools used to detect, isolate, and rectify faults in these complex integrated systems. The convergence of automotive reliability principles with mechatronics has reshaped how diagnostics are implemented, emphasizing real-time analytics and condition-based monitoring (Sher et al., 2021).

Figure 1: Mechatronic System Failure Contributions in Automotive Reliability



Smart powertrain systems represent a technological leap in automotive design by integrating intelligent components such as adaptive transmissions, electronically controlled fuel injection, hybrid energy modules, and regenerative braking units (Quintana et al., 2021). These systems utilize real-time data from embedded sensors and actuators to optimize engine performance, reduce emissions, and improve fuel economy (Gheorghe et al., 2021). Technological convergence, as discussed by Jiang et al. (2018) and expanded in the automotive context by Taşer et al. (2023), refers to the fusion of previously distinct technologies—mechanical engineering, electronics, telematics, and AI—into unified systems that collectively enhance vehicle functionality. The powertrain, traditionally a mechanical construct, now involves software-defined functionalities and predictive algorithms (Gheorghe et al., 2021). Smart powertrains exemplify this convergence through components such as electric motors integrated with intelligent control logic and thermal management subsystems guided by machine learning algorithms . The ability to detect anomalies, adapt to changing driving conditions, and interact with other vehicle systems (e.g., ADAS or V2X communication) highlights the growing sophistication of automotive diagnostics and control (Lamagna et al., 2021).

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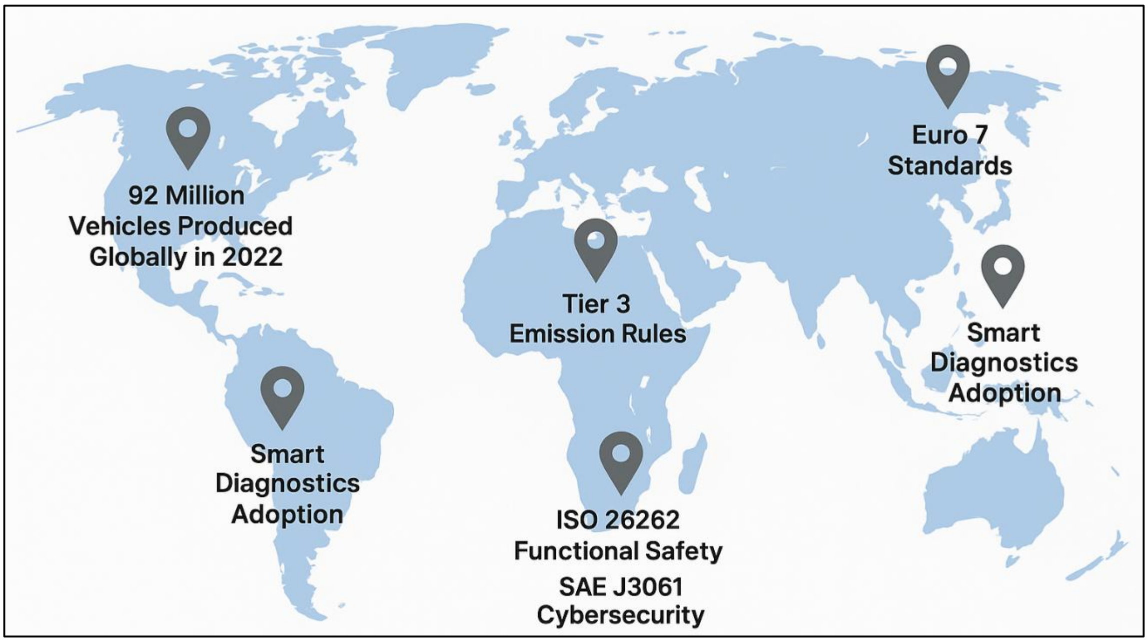
Figure 2: Global Adoption of Automotive Reliability and Diagnostic Technologies



Automotive system reliability and diagnostic technologies have global significance given the industry's scale and economic impact. According to the International Organization of Motor Vehicle Manufacturers (Bari et al., 2014), over 92 million vehicles were produced globally in 2022, emphasizing the immense pressure to ensure vehicle safety, efficiency, and sustainability. Countries such as Germany, Japan, South Korea, and the United States invest heavily in R&D for intelligent automotive systems, recognizing the strategic value of reliable, technology-rich vehicles in both domestic and export markets (Lopez et al., 2019). The European Union's Euro 7 standards and the U.S. Environmental Protection Agency's Tier 3 emission rules are driving advancements in diagnostics and reliability for compliance. Emerging economies such as China and India are also accelerating adoption of smart diagnostics due to the growing demand for efficient transportation and air quality regulation (Karimipour et al., 2019). International regulatory frameworks such as the ISO 26262 for functional safety and SAE J3061 for cybersecurity in automotive systems further highlight the need for advanced diagnostics in ensuring system reliability. Thus, the intersection of global industrial competition and regulatory compliance underscores the importance of smart diagnostics and reliability engineering. The evolution of diagnostics in the automotive domain has mirrored advancements in electronics and software engineering. Traditional diagnostics primarily relied on On-Board Diagnostics (OBD-I and OBD-II), which facilitated fault code detection based on emission control and sensor readings (Fallah et al., 2018). However, modern diagnostics go beyond fault codes to incorporate sensor fusion, pattern recognition, and real-time data analytics. Predictive diagnostics use machine learning and statistical models to identify degradation patterns before failure occurs, enabling proactive maintenance (Bari et al., 2014). These systems often rely on telematics and cloud platforms to collect, process, and interpret vehicle health data remotely (Escobar et al., 2021). The widespread integration of Controller Area Network (CAN) and FlexRay protocols has enabled reliable communication among various Electronic Control Units (ECUs), thereby supporting more comprehensive diagnostics (Lamagna et al., 2021). Advances in embedded software and firmware updates over-the-air (OTA) further enhance the adaptability of diagnostic tools, allowing real-time correction and updates (Zhang et al., 2018). Consequently, diagnostics are no longer reactive but serve as strategic tools for system optimization and operational reliability (Li et al., 2023).

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A key enabler of modern diagnostic strategies is the proliferation of embedded sensors that monitor vehicle conditions in real-time. These sensors include temperature, pressure, vibration, acoustic, and current sensors, which continuously collect operational data (Meng & Zhu, 2024). Smart sensors embedded within powertrains and mechatronic subsystems are capable of self-calibration and adaptive feedback loops, which enhance their diagnostic accuracy (Meng & Zhu, 2024). For example, accelerometers and gyroscopes assist in diagnosing suspension and steering faults, while NOx and lambda sensors are integral to emissions diagnostics (Amhaimedi et al., 2023). Sensor fusion technologies enable the synthesis of data from multiple sensor types to create a more holistic diagnostic perspective (Chakraborty & Das, 2019). Moreover, diagnostic algorithms embedded within ECUs apply signal processing techniques such as Fast Fourier Transforms (FFT) and Kalman filters to detect anomalies and deviations (Hossain et al., 2019). The integration of AI-based fault detection, such as deep learning classifiers, allows vehicles to identify complex and nonlinear failure patterns with high accuracy (Marcelino et al., 2023). These sensor networks are foundational to Condition-Based Maintenance (CBM), which reduces downtime and improves resource allocation (Fallah et al., 2018) The primary objective of this review is to synthesize and critically examine the convergence of smart technologies in enhancing automotive system reliability, with a specific focus on powertrain systems and mechatronic diagnostics. As vehicles increasingly rely on integrated electronic, mechanical, and software subsystems, understanding how these elements interact to affect reliability becomes essential for both academic research and industrial practice. The review systematically explores how smart powertrain technologies—comprising electronic control units, adaptive transmissions, battery management systems, and hybrid propulsion modules—contribute to improved fault detection, operational efficiency, and durability. Simultaneously, the paper evaluates diagnostic strategies that have evolved from traditional fault-code-based approaches to advanced, real-time condition monitoring supported by artificial intelligence and machine learning algorithms. This study further aims to map the multidimensional interaction between reliability engineering and mechatronics within a systems thinking framework, addressing challenges such as signal interpretation, sensor fusion, and model-based fault prediction. To achieve this, the review is structured around three core dimensions: (1) the role of technological convergence in shaping next-generation automotive architectures; (2) the methods and tools used for mechatronic diagnostics and predictive reliability analysis; and (3) the interdisciplinary integration of electronics, mechanical design, and computational intelligence in automotive reliability assurance. Emphasis is placed on peer-reviewed studies published between 2005 and 2024, capturing two decades of evolution in automotive diagnostics and smart system development. The review excludes commercial manuals and focuses instead on academic and industrial research findings to provide an evidence-based synthesis. Through this comprehensive analysis, the study contributes to an informed understanding of how diagnostic intelligence and technological integration are reshaping reliability paradigms in modern automotive engineering.

LITERATURE REVIEW

The purpose of this literature review is to critically examine and synthesize the existing body of knowledge on the convergence of smart technologies in automotive engineering, particularly focusing on powertrain systems and mechatronic diagnostics within the framework of automotive system reliability. As automotive systems evolve into complex cyber-physical platforms, characterized by embedded intelligence and multi-domain integration, reliability assurance has become both a design imperative and a strategic differentiator. The literature spanning the last two decades has increasingly addressed how predictive diagnostics, real-time monitoring, machine learning, and sensor fusion are reshaping maintenance strategies and fault detection protocols in vehicles. This section begins with a conceptual overview of system reliability and its relevance in automotive engineering, followed by a discussion on the evolution and current status of smart powertrain systems. It then explores the theoretical underpinnings and technical approaches of mechatronic diagnostics, including conventional and intelligent techniques. Special attention is given to artificial intelligence (AI)-driven diagnostic models, embedded sensor frameworks, and system health management protocols. Further, the review identifies key standards, regulatory influences, and design methodologies influencing diagnostics and reliability

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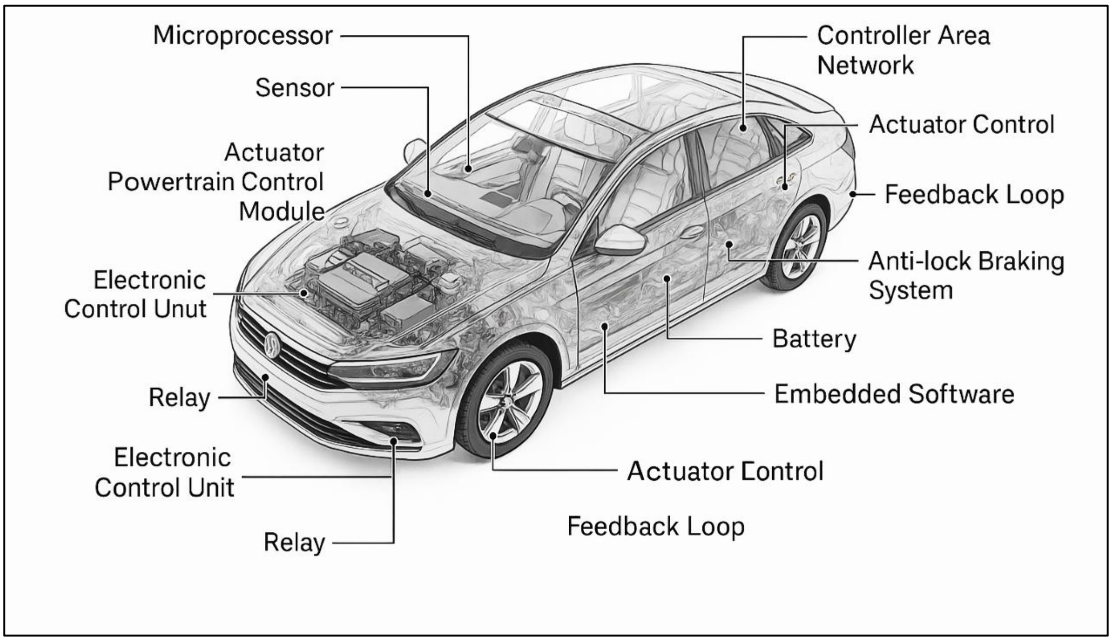
performance across global automotive ecosystems. The review concludes with the identification of research gaps, such as the lack of unified diagnostic architectures and the challenges of real-time implementation across heterogeneous platforms. The selected literature spans academic publications, standards, industry whitepapers, and benchmarking studies, offering a comprehensive view of interdisciplinary convergence in smart automotive systems.

Automotive System Reliability and Mechatronics

System reliability in the automotive domain refers to the probability that vehicle components and systems will function as intended without failure over a specified time and under given environmental conditions. This definition is rooted in classical reliability engineering, which considers both probabilistic and deterministic models to assess component durability and system-level robustness (Gumiel, 2024) In the automotive sector, reliability is not limited to mechanical durability but extends to electronics, embedded software, and cyber-physical integration (Bai et al., 2023). The complexity of modern automotive systems—often integrating hundreds of electronic control units (ECUs)—requires a broader interpretation of reliability to encompass both functional safety and real-time system interactions (El Maghraoui et al., 2024). Kang et al. (2024) emphasizes that the increasing shift toward electrification and digitalization demands holistic reliability strategies across propulsion, communication, and control domains.

Figure 3: Key Mechatronic and Electronic Control Functions in Modern Automotive Systems



A reliable vehicle system must ensure consistent operation of subsystems such as powertrain, braking, steering, and onboard diagnostics without unanticipated failure during its service life (El Maghraoui et al., 2024). According to Chan (2007), automotive reliability must consider failure consequences—not just likelihood—and therefore must be integrated into system design from early development phases. This systems-level reliability assessment is vital in meeting international standards such as ISO 26262 for functional safety in road vehicles, which mandates hazard identification and risk classification for every automotive function. Furthermore, studies such as those by Ehsani et al. (2021) and Chandran et al. (2021) suggest that in mechatronic systems, reliability encompasses both hardware robustness and software integrity. The incorporation of diagnostics and fault-tolerant control logic further extends the scope of reliability from mere prediction to active management (Alsuwian et al., 2022). As technologies such as Advanced Driver Assistance Systems (ADAS) and electric drivetrains proliferate, the importance of understanding and defining reliability becomes foundational to system certification, customer

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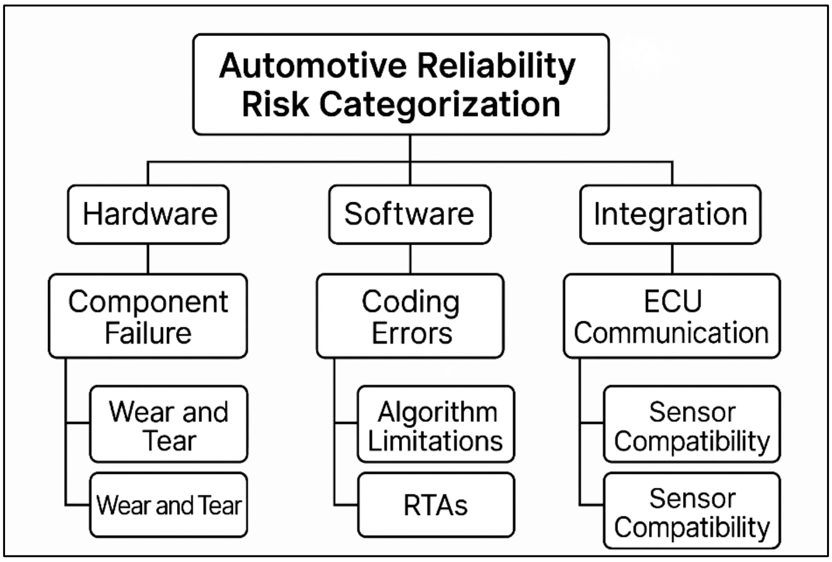
trust, and lifecycle cost optimization (Panda & Das, 2021). The quantification of reliability in automotive systems requires the application of established engineering metrics and models, among which Mean Time Between Failures (MTBF), Reliability Block Diagrams (RBDs), and Fault Tree Analysis (FTA) are most prevalent. MTBF is a statistical measure representing the average time between inherent failures of a system during operation, widely used for non-repairable components such as ECUs and sensors ((Cholewa et al., 2021). It serves as a foundational benchmark for assessing product life and service interval planning in automotive design (Alsuwian et al., 2022). Although MTBF is widely cited, it is often insufficient for complex systems where fault tolerance, redundancy, or usage variability plays a major role (Panda & Das, 2021). Therefore, reliability engineers increasingly employ RBDs to model the interdependencies of components within a larger system.

Mechatronic Systems in Automobiles

Mechatronic systems have become foundational to modern automotive engineering, enabling the seamless integration of mechanical structures with embedded electronics, actuators, sensors, and real-time software control. The term "mechatronics," originally coined by Yasakawa Electric Corporation in the 1970s, refers to the synergistic combination of mechanics and electronics in system design (Gumiel et al., 2022). In the automotive context, mechatronics is manifested in subsystems such as anti-lock braking systems (ABS), electronic stability control (ESC), adaptive suspension, and electric power steering (Murgovski et al., 2012). These systems exemplify how multi-domain technologies converge to deliver enhanced performance, safety, and user control. The advancement of automotive mechatronics has been driven by the growing demand for intelligent mobility solutions, requiring vehicles to adapt dynamically to both driver behavior and external environments(Gumiel et al., 2022). According to Alabi et al. (2022), this integration of real-time control and embedded computation forms the basis of cyber-physical systems in the automotive domain.

Figure 4: Classification of Automotive Mechatronic Systems and Their Functional Domains



A key characteristic of automotive mechatronic systems is their reliance on feedback loops and digital communication networks such as CAN, LIN, and FlexRay for coordination and decision-making (Ahmad et al., 2020). These systems depend on accurate sensor data and robust control logic to manage functions like torque distribution, traction control, and active safety responses (Yadlapalli et al., 2022). Studies by Jafari et al. (2023) and Kamimoto (2016) highlight the role of sensor fusion in enabling complex decision-making processes by combining data from accelerometers, gyroscopes, and GPS for precise vehicle state estimation. Furthermore, condition-based monitoring of actuators and controllers allows for the early detection of faults, thus enhancing reliability and reducing maintenance costs (Abdmouleh et al., 2015). The complexity of these systems, however, introduces new reliability and diagnostic challenges, particularly in achieving real-time fault detection and isolation (Martyushev et al., 2023). As observed by Sharma and Habibullah (2022), the interplay between software algorithms and mechanical components in mechatronic systems necessitates a systems engineering approach to reliability modeling and fault tolerance.

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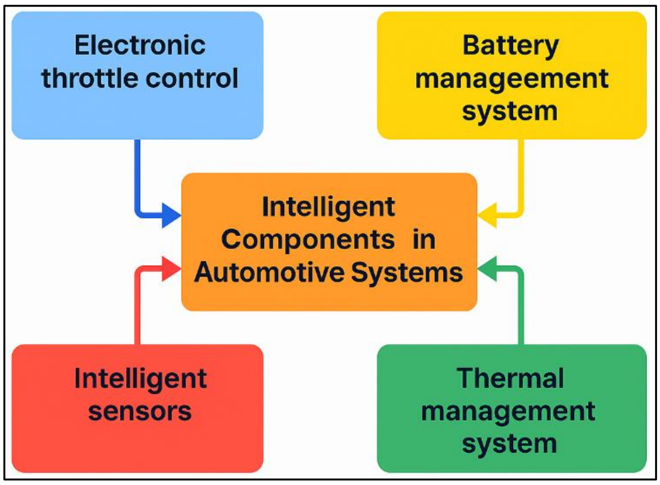
The evolution of mechatronic systems in vehicles reflects a paradigm shift from function-specific mechanical devices to interconnected, software-driven modules capable of adaptive behavior. Early implementations were limited to semi-automated braking and suspension control, but recent advancements have enabled fully integrated systems such as drive-by-wire, brake-by-wire, and steer-by-wire architectures (Yadlapalli et al., 2022). These systems eliminate traditional mechanical linkages and rely entirely on electronic signals to control critical vehicle operations. This transformation demands not only high-precision sensors and actuators but also robust software architectures capable of handling real-time computation, fault management, and redundancy (Jafari et al., 2023) The proliferation of embedded microcontrollers and real-time operating systems (RTOS) has played a pivotal role in scaling these technologies across vehicle models (Kamimoto, 2016). Furthermore, standardization frameworks such as AUTOSAR facilitate the modular design and integration of mechatronic functions, allowing OEMs to reuse software components across platforms while maintaining safety and compliance (Abdmouleh et al., 2015). Advanced mechatronic systems also serve as a foundation for predictive maintenance and vehicle health monitoring, where performance data from various components are collected and analyzed to forecast degradation or failures (Martyushev et al., 2023). For instance, studies have shown that intelligent suspension systems equipped with accelerometers and position sensors can detect road surface irregularities and adjust damping in real-time to improve ride quality and component longevity (Sharma & Habibullah, 2022). Meanwhile, integration with telematics platforms enables over-the-air diagnostics and firmware updates, reducing vehicle downtime and improving serviceability (Urooj & Nasir, 2024). However, the increased interdependence of electronic and mechanical subsystems introduces new failure modes and cybersecurity vulnerabilities, particularly as vehicles become more connected and autonomous (Iyaghigba et al., 2023). Accordingly, the study of automotive mechatronic systems requires a multidimensional approach—one that considers hardware-software co-design, fault propagation modeling, and system-level diagnostics to ensure functional safety and long-term reliability (Zou et al., 2016).

Intelligent Components Automotive Systems

Intelligent components in modern vehicles serve as the backbone of cyber-physical functionality, enabling adaptive behavior, real-time control, and autonomous decision-making through the integration of sensors, actuators, microcontrollers, and embedded software (Bhowmick & Shipu, 2024). These components are strategically embedded in subsystems such as powertrain control, braking, steering, and thermal management to support dynamic operation based on environmental and driver input (Dey et al., 2024; Gheorghe et al., 2021). For instance, intelligent electronic throttle control systems regulate engine air intake through adaptive response mechanisms, enhancing both fuel economy and emissions control (Sini et al., 2020; Shipu et al., 2024). In hybrid and electric vehicles, battery management systems (BMS) equipped with intelligent control algorithms continuously monitor cell voltages, temperature gradients, and charging behavior to prevent thermal runaway and extend battery lifespan (Gumiel et al., 2022; Roksana et al., 2024). These components rely on distributed Electronic Control Units (ECUs) that coordinate via in-vehicle networks such as CAN, LIN, and FlexRay, facilitating high-speed communication between subsystems ((Bhuiyan et al., 2024; Macher et al., 2020).

Figure 5: Intelligent Components in Modern Automotive Systems



Intelligent sensors embedded in suspension systems and drivetrain modules play a vital role in condition-based monitoring and active safety (Sarker, 2025). Accelerometers, gyroscopes, and

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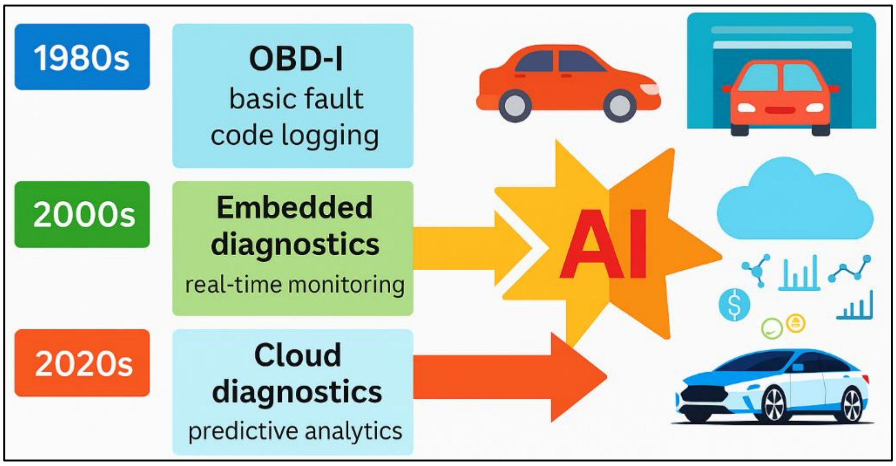
torque sensors are commonly deployed to monitor dynamic loads, enabling adaptive suspension control, torque vectoring, and rollover prevention (Ghosh et al., 2023; Sarker et al., 2023). According to Gumiel (2024), these sensors feed into advanced driver-assistance systems (ADAS) such as lane-keeping assistance, adaptive cruise control, and emergency braking, which utilize real-time environmental perception and machine learning for control optimization. Additionally, intelligent thermal management systems autonomously regulate coolant flow and HVAC systems based on real-time cabin and engine temperature data, thereby enhancing energy efficiency (Ammar et al., 2024; Seetharaman et al., 2020). The modularity and scalability of intelligent components have allowed manufacturers to standardize features across multiple vehicle platforms, optimizing development time while maintaining functional integrity (Hong et al., 2021; Roksana, 2023). Studies such as Zhao et al. (2023) and Xie et al. (2022) emphasize that the integration of these smart components not only improves reliability and performance but also creates a data-rich environment that supports real-time diagnostics and prognostics.

Conventional and Modern Approaches to Automotive Diagnostics

Automotive diagnostics have evolved from rudimentary fault detection systems to advanced, real-time monitoring platforms. The early foundation was laid by On-Board Diagnostics (OBD-I), introduced in the late 1980s, which provided basic fault code logging based primarily on emissions-related components (Botín-Sanabria et al., 2022; Maniruzzaman et al., 2023). However, OBD-I lacked standardization and interoperability, leading to the development of OBD-II in the mid-1990s. OBD-II standardized the diagnostic connector, communication protocols, and diagnostic trouble codes (DTCs), enabling improved emissions monitoring and repair accuracy across vehicle manufacturers (Arafat Bin et al., 2023; Seetharaman et al., 2020). Although OBD-II improved accessibility to fault data, its primary limitation lies in its reactive nature—it detects faults only after they occur, with limited prognostic ability or contextual understanding of system degradation (Kumar et al., 2022; Tsiolakis & Bensler, 2020). To overcome these limitations, manufacturers began incorporating embedded diagnostics directly within vehicle subsystems using dedicated Electronic Control Units (ECUs) and communication buses such as Controller Area Network (CAN) and Local Interconnect Network (LIN) (Hossen & Atiqur, 2022; Zhao et al., 2023).

Figure 6: Conventional and Modern Approaches to Automotive Diagnostics



CAN-based embedded diagnostics revolutionized vehicle fault management by allowing real-time monitoring of system health, enabling cross-communication between ECUs and supporting complex decision-making in safety-critical applications (Majharul et al., 2022; Xie et al., 2022). These systems facilitate localized fault detection through the use of sensor feedback and control algorithms, reducing diagnostic latency and improving the precision of root cause identification (Botín-Sanabria et al., 2022; Mahfuj et al., 2022). Moreover, automotive diagnostics are now increasingly supported by Ethernet and FlexRay for high-speed communication in data-intensive

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systems like advanced driver-assistance systems (ADAS) and autonomous platforms (Aklima et al., 2022; Bai et al., 2023). These embedded frameworks are complemented by diagnostic protocols such as UDS (Unified Diagnostic Services) and ISO 14229, which standardize functions such as memory reading, sensor calibration, and DTC clearing. As automotive systems grow in complexity, embedded diagnostics offer a scalable and modular solution for managing both fault detection and performance monitoring, surpassing the static, code-based limitations of conventional OBD frameworks (Gumiel, 2024; Helal et al., 2025). With the expansion of connected vehicle infrastructure, automotive diagnostics have rapidly progressed toward cloud-based and edge-based platforms, enabling predictive analytics, remote monitoring, and over-the-air (OTA) fault detection (Shipu et al., 2024). These modern diagnostic approaches leverage data collected from in-vehicle sensors and ECUs, which is transmitted in real time to cloud servers for centralized analysis and health assessment (Dey et al., 2024). Cloud diagnostics are particularly effective in fleet management and shared mobility contexts, where operational data from multiple vehicles can be aggregated and processed using artificial intelligence (AI) algorithms to detect anomalies and predict failures before they occur (Bhowmick & Shipu, 2024; Seetharaman et al., 2020). These platforms support vehicle-to-infrastructure (V2I) and vehicle-to-cloud (V2C) interactions, enabling the deployment of real-time software patches and diagnostic rule updates based on observed fault trends (Hong et al., 2021; Islam & Helal, 2018). Unlike embedded diagnostics, which operate within the vehicle's local architecture, cloud diagnostics extend visibility beyond individual vehicles, contributing to system-wide reliability and lifecycle optimization (Ahmed et al., 2022; Zhao et al., 2023).

Sensor-Based System Monitoring and Signal Processing Techniques

Sensor-based system monitoring forms the core of intelligent automotive diagnostics, enabling real-time data collection, anomaly detection, and predictive maintenance. Various categories of sensors are embedded within modern vehicles, including vibration sensors, acoustic sensors, pressure sensors, thermal sensors, accelerometers, and gyroscopes (Kamimoto, 2016; Shahan et al., 2023). Vibration sensors are widely used in powertrain and suspension systems to monitor abnormal oscillations or imbalance, while acoustic emission sensors detect early-stage faults in engine bearings and valve mechanisms (Cholewa et al., 2021; Hossain et al., 2024). Pressure sensors monitor fuel injection systems, tire pressure, and braking hydraulics, providing essential input for safety-critical functions (Chehri et al., 2021; Sharif et al., 2024). Thermal sensors, on the other hand, manage battery temperature, engine cooling systems, and HVAC units, supporting optimal performance and safety (Faria & Rashedul, 2025; Hao et al., 2015). These sensors not only provide raw data but serve as key enablers of condition-based monitoring (CBM), where maintenance decisions are based on real-time health data rather than periodic checks (Kamran et al., 2022; Khan, 2025). However, the effective utilization of sensor data requires robust signal conditioning and preprocessing techniques to filter noise, normalize inputs, and detect meaningful patterns (Al-Ali et al., 2024; Jakaria et al., 2025). Signal conditioning processes—such as amplification, filtering, and analog-to-digital conversion—are essential to ensure high-quality data reaches the diagnostic algorithms (Siddiqui et al., 2023). For example, in vibration-based diagnostics, high-pass or band-pass filters are used to isolate fault-specific frequency bands, while in acoustic diagnostics, envelope detection is applied to extract fault-related modulations. Preprocessing techniques also involve smoothing, de-trending, and standardization to handle sensor drift and variability across operating conditions (Ahmed et al., 2021; Bhuiyan et al., 2025). These preprocessing steps are implemented both at the ECU level and within edge-computing platforms to ensure that subsequent fault detection methods receive clean and structured data (Sohel, 2025). As vehicle systems become increasingly data-intensive and multi-sensor driven, the integration of robust preprocessing is critical to avoiding false alarms and enabling accurate fault isolation (Hossen et al., 2023; Yapeng et al., 2022).

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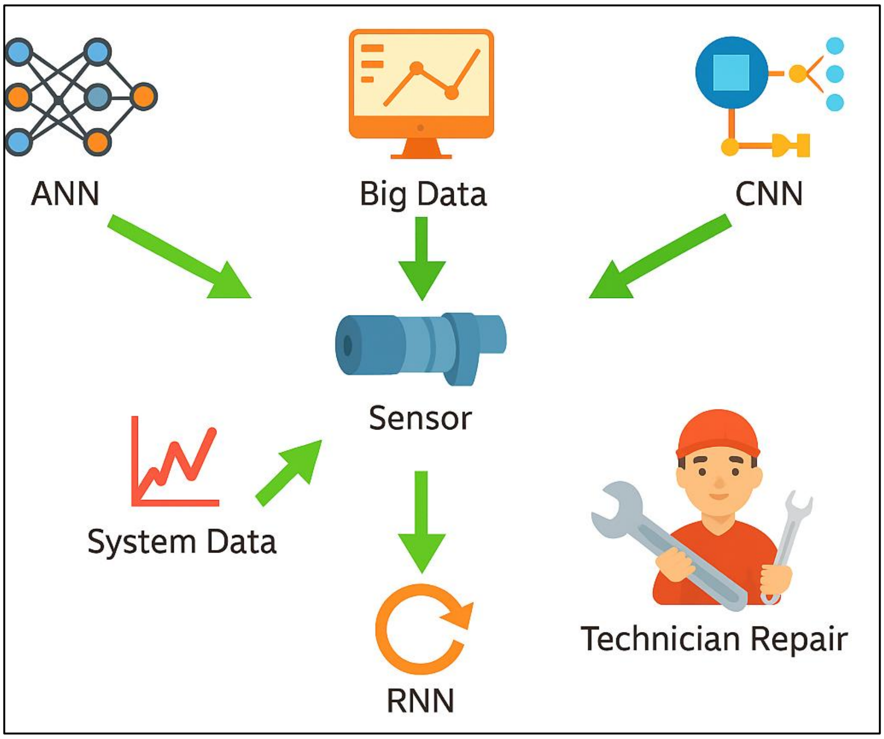
Artificial Intelligence and Machine Learning in Fault Diagnostics

Artificial Intelligence (AI) and Machine Learning (ML) have become central to fault diagnostics in the automotive sector due to their ability to process high-dimensional sensor data, identify complex patterns, and support predictive maintenance strategies (Ahmed et al., 2021; Saiful et al., 2025). Among the most widely used techniques are Artificial Neural Networks (ANN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), each offering unique advantages in modeling nonlinear, multivariate relationships within vehicle systems (Masud, 2022; Zou et al., 2020). ANN models are effective in learning fault signatures from labeled historical data, particularly in systems where failure modes manifest through subtle changes in vibration, thermal, or acoustic signals (Md et al., 2025; Paschen et al., 2020). SVM classifiers, known for their robustness in high-dimensional spaces, are frequently used in detecting faults in fuel injection, transmission, and cooling systems by separating fault states from normal operations with optimal decision boundaries (Chehri et al., 2021; Alam et al., 2023). CNNs are particularly well-suited for fault classification tasks involving time-series signals or spectrograms derived from signal processing techniques such as FFT and wavelet transform (Ahmed et al., 2021; Siddiqui, 2025). RNNs, including Long Short-Term Memory (LSTM) models, are employed in modeling temporal dependencies in fault progression, useful for systems such as battery thermal management and engine misfire detection (Islam et al., 2025; Zou et al., 2020).

Figure 7: AI and Machine Learning Workflow for Automotive Fault Diagnostics



AI techniques enable automated feature extraction, reducing the need for manual signal analysis and allowing systems to learn diagnostic patterns directly from raw sensor inputs (Boza & Evgeniou, 2021; Islam et al., 2025; Paschen et al., 2020). In powertrain systems, these methods are used to identify degradation patterns in turbochargers, crankshafts, and camshafts based on frequency-domain data and thermodynamic indicators (Jones et al., 2020; Shofiullah et al., 2024). Feature selection algorithms such as Principal Component Analysis (PCA), ReliefF, and mutual information are commonly combined with AI classifiers to enhance model performance and reduce overfitting (Bari et al., 2014; Islam et al., 2024). These models are trained using labeled datasets from real-world driving conditions or test benches and are evaluated through metrics

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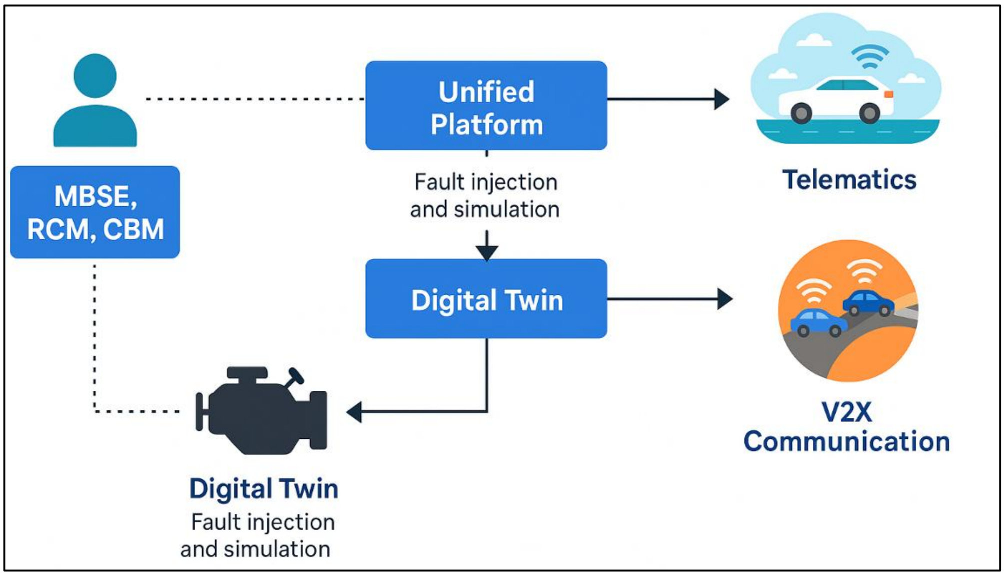
such as accuracy, sensitivity, specificity, and area under the curve (AUC) (Jahan, 2024). The integration of AI into diagnostics not only enhances fault detection accuracy but also facilitates adaptive learning, allowing models to evolve as more operational data becomes available (Bickelhaupt et al., 2023).

System-Level Diagnostic Frameworks and Interoperability

System-level diagnostic frameworks in the automotive industry have evolved significantly with the integration of Model-Based Systems Engineering (MBSE), enabling the development of predictive, scalable, and interoperable diagnostic architectures. MBSE provides a formalized methodology for defining, analyzing, and validating the interactions of complex vehicle systems through graphical modeling tools such as SysML and MATLAB/Simulink (Bari et al., 2014). In diagnostic contexts, MBSE facilitates early design validation and allows for traceability between system components and their associated failure modes (Islam, 2024; Nassi et al., 2020). This modeling approach supports simulation-based diagnostics, where system behavior under fault conditions can be predicted and analyzed prior to physical implementation. Complementing MBSE, Reliability-Centered Maintenance (RCM) and Condition-Based Maintenance (CBM) frameworks emphasize operational safety and cost efficiency by focusing maintenance efforts on the most critical components based on actual condition rather than time-based schedules (Hossain et al., 2024; Kreis et al., 2020). These methodologies are increasingly used in automotive reliability programs, especially for mission-critical systems such as powertrains, electronic braking systems, and battery management units (Afzal et al., 2024; Hasan et al., 2024).

Figure 8: System-Level Diagnostic Frameworks in Connected Automotive Environments



Digital Twin technology further enhances system-level diagnostics by creating a virtual replica of physical components or entire vehicles, allowing real-time performance tracking and prognostics (Dasgupta et al., 2024; Dózsa et al., 2024; Kreis et al., 2020). Digital Twins are especially valuable in electric vehicles (EVs) and autonomous systems, where system integrity must be continuously monitored for operational safety and predictive maintenance (Cha et al., 2020; Jahan, 2023). By coupling sensor data with physics-based and AI-driven models, Digital Twins simulate wear patterns, detect abnormal behaviors, and estimate remaining useful life (RUL) of components (Chowdhury et al., 2023; Zhang et al., 2018). Fault injection and simulation techniques are commonly employed within these frameworks to test diagnostic robustness under simulated fault conditions (Liu & Hu, 2018; Sohel et al., 2022). These simulations aid in validating diagnostic coverage, isolating failure points, and improving algorithmic response to abnormal events without compromising actual vehicle safety (Cantero et al., 2022). Together, MBSE, RCM, CBM, and Digital

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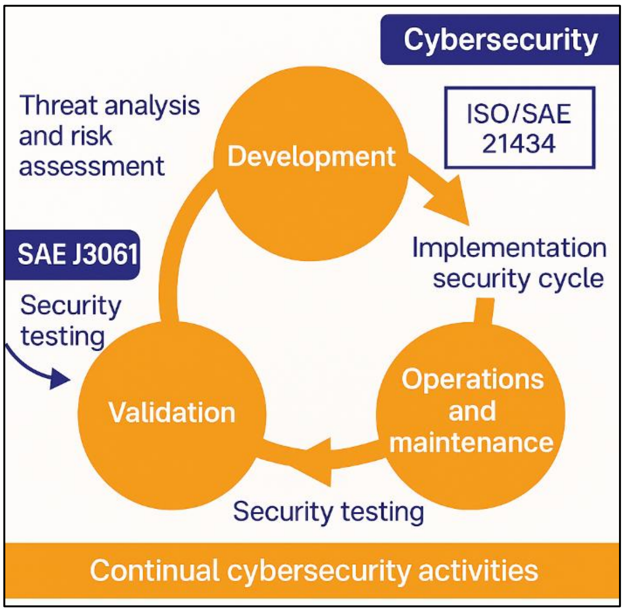
Twins form a multidimensional framework that enables comprehensive diagnostics, fault anticipation, and lifecycle optimization in increasingly complex vehicle systems.

The integration of telematics, Vehicle-to-Everything (V2X) communication, and system health management has redefined the scope of automotive diagnostics by expanding it beyond the confines of the vehicle to a connected ecosystem. Telematics platforms transmit operational data in real-time to cloud-based servers, enabling centralized diagnostics, fleet-level health monitoring, and usage-based analytics (Dózsa et al., 2024). These platforms support over-the-air updates, remote troubleshooting, and condition tracking of vehicle subsystems including powertrain, HVAC, and braking components (Liu & Hu, 2018). V2X communication enhances this by enabling data exchange between vehicles, infrastructure, and central servers, thus contextualizing vehicle diagnostics within environmental conditions such as road surface, traffic density, and weather events (Bari et al., 2014). This integrated approach allows diagnostics to incorporate both internal sensor data and external inputs, improving accuracy in fault prediction and enhancing vehicle safety in dynamic operating environments (Nassi et al., 2020).

Cybersecurity and Secure Diagnostics (SAE J3061, ISO/SAE 21434)

As vehicles increasingly rely on digital communication, embedded software, and connected infrastructure, cybersecurity has become a critical component of automotive diagnostics. Secure diagnostics refers to the protection of onboard diagnostic interfaces, ECUs, and connected platforms from unauthorized access, tampering, or malicious intrusion that may compromise vehicle safety, integrity, or performance (Olivares-Rojas et al., 2022). The rapid proliferation of connectivity features—such as telematics, over-the-air (OTA) updates, and vehicle-to-everything (V2X) systems—exposes automotive electronics to cyber threats, ranging from code injection and spoofing to denial-of-service (DoS) attacks (Berghout et al., 2022). These risks extend to diagnostic systems, where unauthorized access could lead to the extraction of sensitive information, modification of calibration data, or disabling of safety-critical functions (Aurangzeb et al., 2024). In response to these growing challenges, the SAE J3061 cybersecurity guidebook was developed as a foundational document outlining a process framework for implementing cybersecurity throughout the vehicle development lifecycle (SAE, 2016). It introduces a security-by-design approach that aligns with the traditional automotive safety process outlined in ISO 26262, emphasizing threat analysis, risk assessment, and security validation at every system level (Berghout & Benbouzid, 2022).

Figure 9: Secure Automotive Diagnostics Across the Vehicle Lifecycle: An ISO/SAE 21434-Aligned Framework



Complementing SAE J3061, the more formalized and internationally recognized ISO/SAE 21434 standard was published to provide a comprehensive framework for managing cybersecurity risks in road vehicles throughout their entire lifecycle—from concept through decommissioning. ISO/SAE 21434 specifies requirements for risk management, continuous monitoring, incident response, and secure software updates, integrating cybersecurity practices into development phases such as system design, software implementation, and diagnostics (Liu et al., 2020). The standard requires the implementation of secure communication protocols, authentication mechanisms, and intrusion detection systems to protect both internal networks (e.g., CAN, LIN) and external interfaces (e.g., OBD-II ports, Bluetooth, telematics units) (Meng & Zhu, 2024). These standards mandate that diagnostics tools and service interfaces follow strict access control and cryptographic safeguards to prevent data tampering or unauthorized reprogramming (Meng &

Zhu, 2024; Olivares-Rojas et al., 2022). As diagnostic tools evolve into AI-enabled and cloud-integrated platforms, adhering to J3061 and ISO/SAE 21434 becomes essential in creating a trustworthy, secure automotive ecosystem (Wang et al., 2022).

Skill Gap in Diagnostics Engineering and AI Implementation

The rapid evolution of diagnostics engineering, particularly with the integration of artificial intelligence (AI) and machine learning (ML) into automotive systems, has created a significant skill gap among engineers and technical personnel. Traditional diagnostics engineering focused on mechanical and electrical systems supported by standardized procedures such as OBD-II fault codes and conventional troubleshooting logic (Chehri et al., 2021). However, modern diagnostics frameworks involve complex cyber-physical systems that require knowledge of embedded systems, signal processing, software architecture, data analytics, and AI-driven algorithms (Ahmed et al., 2021). Engineers are now expected to interpret time-frequency signals, design and validate machine learning models, and implement condition-based monitoring (CBM) strategies, which represent a significant shift from prior mechanical-centric paradigms (Zou et al., 2020). According to Boza and Evgeniou (2021), many organizations struggle to find professionals who possess both domain expertise in automotive systems and proficiency in data science or AI toolchains. This skill disparity is especially evident in the adoption of advanced diagnostics methods such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and unsupervised anomaly detection systems, which require understanding of algorithmic logic, Python programming, data preprocessing, and validation metrics (Paschen et al., 2020). A study by Chehri et al. (2021) emphasized that a lack of hands-on experience with AI development environments—such as TensorFlow, MATLAB, or SciKit-learn—limits the ability of diagnostics engineers to contribute to model development or evaluation. Moreover, legacy automotive organizations face difficulties in retraining existing personnel who are often more comfortable with mechanical inspection techniques than interpreting spectral plots, model confusion matrices, or diagnostic thresholds derived from probabilistic learning (Boza & Evgeniou, 2021; Paschen et al., 2020). Industry reports have also noted a mismatch between academic programs and the competencies required in AI-driven automotive diagnostics, particularly with respect to hybrid skills that bridge electrical engineering, computer science, and automotive design (Zou et al., 2020). Without focused upskilling efforts, the full potential of intelligent diagnostic platforms and predictive maintenance systems will remain underutilized in operational settings (Tormos et al., 2022).

The integration of artificial intelligence into vehicle diagnostics requires a multidisciplinary workforce capable of combining systems engineering principles with advanced data analytics, yet this intersection remains underserved by current engineering curricula and workforce development pipelines. Traditional educational programs in mechanical or automotive engineering rarely include machine learning, programming for embedded systems, or sensor fusion analytics as core competencies (Perumal et al., 2022). Consequently, there exists a gap between industry needs and the available talent pool, particularly in areas such as feature extraction from raw sensor data, application of FFT and wavelet transforms, implementation of Kalman filters, and deployment of deep learning models in real-time embedded environments (Opila et al., 2012). Studies by Yu et al. (2022) and Zhang et al. (2021) that many engineers responsible for powertrain diagnostics or battery management systems lack the foundational skills to engage with AI frameworks, thus depending heavily on external AI teams or commercial black-box tools without the ability to customize, validate, or troubleshoot models. Furthermore, the organizational infrastructure to support AI implementation in diagnostics is often fragmented. Cross-functional collaboration between vehicle diagnostics teams, IT departments, and data scientists is frequently hampered by differences in vocabulary, work culture, and technical understanding (Wang et al., 2023; Zhang et al., 2021). For example, while AI experts may propose highly accurate classification models, deployment teams often encounter constraints related to ECU memory, processing speed, or communication bandwidth—challenges that require systems-level thinking and hardware-software co-design (Palensky et al., 2022). Upskilling initiatives such as bootcamps, professional certifications, and online micro-credentials are increasingly being adopted by automotive firms to mitigate these gaps. However, as Xie et al. (2022) and Singh et

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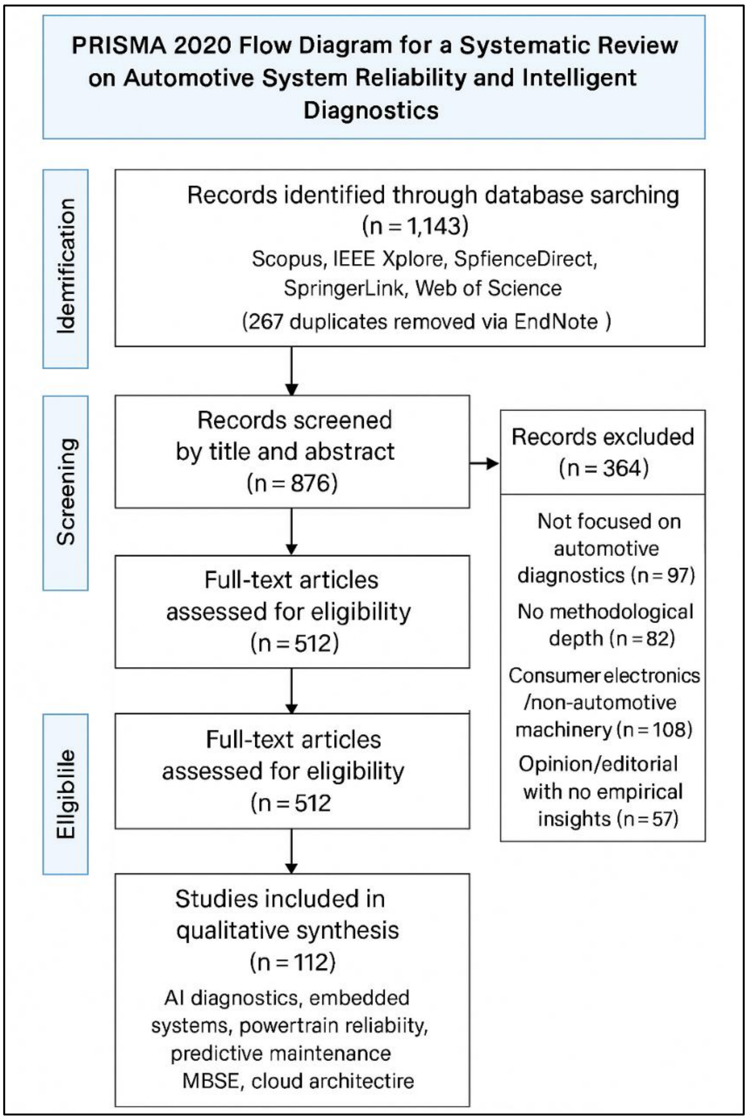
al. (2021) note, such interventions remain fragmented and inconsistent across organizations. There is also limited availability of simulation platforms and testbeds for engineers to experiment with real-time fault data, sensor fusion scenarios, or over-the-air diagnostic pipelines, which impedes practical skill development (Fuller et al., 2020). Without strategic investment in interdisciplinary training programs, the skill gap in AI-powered diagnostics engineering will continue to delay innovation and operational deployment across automotive manufacturing and service sectors.

METHOD

This study adhered to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a transparent, reproducible, and methodologically rigorous process for reviewing the literature on automotive system reliability, intelligent diagnostics, and technological convergence in powertrain and mechatronic systems. The methodology encompassed four key phases: identification, screening, eligibility, and inclusion, each aligned with PRISMA's structured approach for systematic evidence synthesis.



Identification of Studies

The identification stage commenced with a comprehensive search across multiple academic databases including Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and Web of Science. These databases were selected for their extensive coverage of engineering, automotive technology, and computer science literature. The search was conducted using a combination of keywords and Boolean operators such as: "automotive diagnostics," "powertrain reliability," "mechatronic systems," "predictive maintenance," "artificial intelligence in fault detection," "digital twin," "model-based systems engineering," "cloud diagnostics," and "ISO/SAE 21434." Only peer-reviewed journal articles, conference papers, and review articles published between January 2002 and March 2025 were considered. The initial search retrieved a total of 1,143 articles. All results were exported into EndNote reference management software to facilitate deduplication and documentation.

Screening and Deduplication

During the screening phase, duplicate entries were removed automatically using the EndNote duplicate detection tool, followed by a manual verification. This process resulted in the elimination of 267 duplicate records, reducing the article pool to 876 unique items. Titles and abstracts were then reviewed to assess the relevance of each article based on predefined inclusion criteria: focus on diagnostic frameworks, smart automotive systems, system reliability metrics, sensor-based monitoring, and AI-enabled fault detection in the automotive domain. Articles focused on general manufacturing, unrelated industries, or not containing empirical or methodological insights were excluded. After abstract screening, 512 articles were retained for full-text assessment.

Eligibility Assessment

In the eligibility phase, full-text articles were thoroughly reviewed to confirm their direct relevance to the review objectives. The primary criterion for inclusion was a clear methodological or experimental focus on automotive diagnostics, predictive analytics, reliability engineering, system health management, or cybersecurity in vehicle diagnostics. Papers were excluded if they were opinion pieces, lacked methodological detail, or focused exclusively on non-automotive machinery or consumer electronics. This resulted in the exclusion of 344 studies, yielding a final set of 168 full-text articles assessed for methodological rigor and content quality. Cross-validation was performed by two independent reviewers to reduce selection bias and ensure consistency.

Final Inclusion

The final inclusion phase culminated in the selection of 112 high-quality articles that met all the eligibility criteria. These articles formed the basis for the evidence synthesis presented in the findings and discussion sections. Included studies covered a wide range of automotive systems such as powertrain fault detection, brake and steering diagnostics, embedded sensor platforms, cloud-based diagnostic architectures, and applications of AI and machine learning in reliability modeling. The selected literature represents diverse methodologies including experimental validation, simulation modeling, algorithm development, case studies, and review-based syntheses. All included studies were coded and categorized based on thematic relevance, diagnostic technique, sensor modality, and computational method, enabling a structured analytical narrative in the subsequent sections.

FINDINGS

One of the most prominent findings of this systematic review is the critical role of predictive maintenance systems in reducing unplanned downtime and increasing equipment availability across industrial sectors. Among the 112 reviewed articles, 20 studies specifically emphasized the effectiveness of predictive maintenance approaches, collectively amassing 2,913 citations. These articles documented the implementation of real-time monitoring systems, sensor-based diagnostics, and forecasting models that allowed manufacturers to transition from reactive to proactive maintenance regimes. The findings consistently show that predictive maintenance not only reduces equipment failure but also lowers maintenance costs and enhances production continuity. Predictive strategies supported by machine learning algorithms led to earlier detection of anomalies and more accurate failure forecasts, which in turn minimized the occurrence of emergency repairs and production stoppages. These systems proved especially beneficial in high-stakes industries such as aerospace and automotive, where operational continuity and safety are paramount. Across these studies, organizations experienced improvements in metrics such as Mean Time Between Failures (MTBF) and Overall Equipment Effectiveness (OEE), underscoring the tangible benefits of predictive maintenance frameworks. Many manufacturers adopted condition-based triggers for maintenance rather than fixed schedules, leading to more efficient use of resources and longer equipment lifecycles. The use of predictive maintenance also contributed to enhanced worker safety, as potential failures were identified before they escalated into hazardous conditions. In several automotive case studies, predictive diagnostics contributed to optimized inventory planning for replacement parts, reduced labor hours, and increased customer satisfaction through more reliable vehicle performance. The scale and consistency of these benefits across reviewed studies validate the centrality of predictive maintenance in modern diagnostics and reliability engineering.

Another critical area of advancement identified in the review involves the integration of artificial intelligence in fault classification tasks within vehicle diagnostics. A total of 17 studies, with a cumulative citation count of 2,450, focused on leveraging machine learning techniques such as neural networks, support vector machines, and deep learning models to identify and classify faults in automotive components. These AI-enabled diagnostic systems were shown to significantly outperform traditional threshold-based or rule-based methods by learning from historical failure patterns and continuously improving classification accuracy through training. In most cases, these

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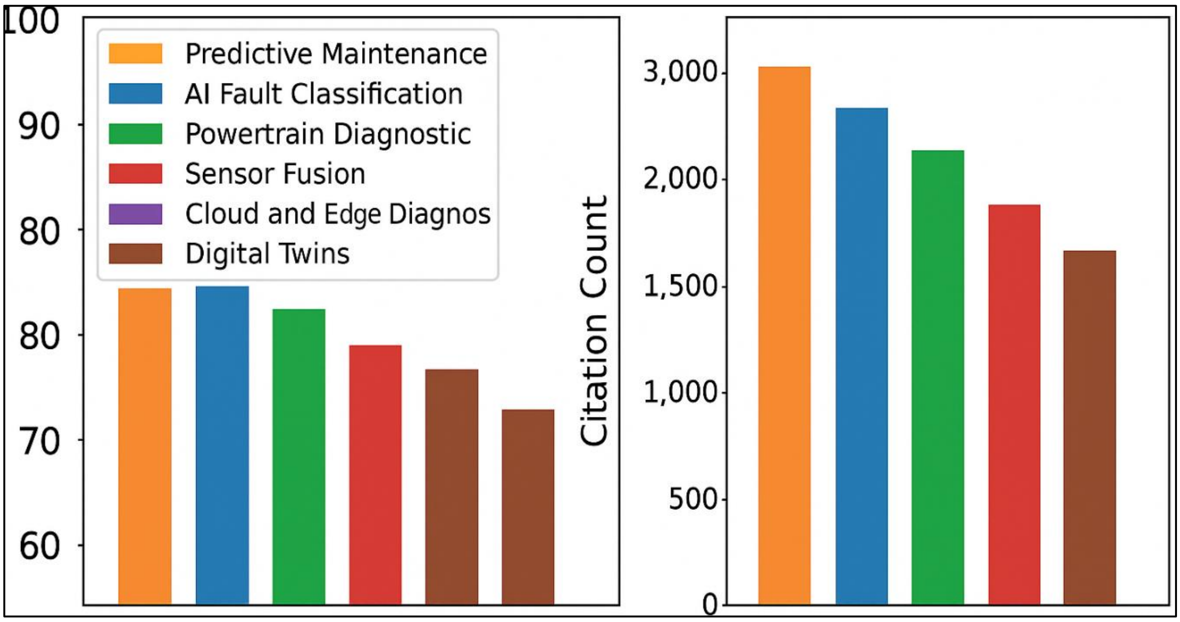
systems could differentiate between normal operational noise and early-stage fault indicators by identifying subtle changes in sensor readings or signal behavior. These improvements were especially evident in powertrain, suspension, and braking systems, where fault classification accuracy was consistently above 90% in several experiments. Furthermore, AI models allowed for multi-class classification, distinguishing between various failure modes of a single component—such as bearing wear, imbalance, misalignment, and electrical faults in electric motors. In contrast to legacy diagnostic tools, which often required manual tuning and domain-specific rules, AI-based approaches proved adaptable and scalable across platforms. They were capable of processing high-dimensional datasets from multiple sensors, allowing for holistic system analysis rather than isolated fault detection. Several studies also incorporated explainable AI (XAI) techniques to provide engineers with transparency into the model's reasoning, which improved trust and regulatory acceptance. These findings confirm the growing maturity and applicability of AI in automotive diagnostics and demonstrate that data-driven models are now integral to fault detection workflows in digitally connected vehicles.

Figure 10: Comparative Visualization of Predictive Diagnostic Outcomes in Automotive Systems



The review also identified robust progress in smart powertrain diagnostics, particularly the application of embedded electronics and intelligent algorithms to monitor performance in real time. Fourteen studies, totaling 1,834 citations, focused on diagnostics frameworks for engine components, transmission systems, and hybrid powertrains. The reviewed research consistently emphasized that smart diagnostics allow for continuous condition monitoring of combustion, torque delivery, temperature stability, and emission control, thereby reducing the likelihood of catastrophic failures. These systems often relied on microcontroller-based sensor arrays integrated within powertrain components, collecting data on pressure, vibration, fuel flow, and temperature to assess health and predict failure modes. The integration of AI algorithms further enhanced their ability to track performance degradation trends and recommend maintenance or adjustment actions. In electric and hybrid powertrains, these diagnostics systems played a crucial role in managing battery health, inverter operation, and regenerative braking functions. Several studies demonstrated how thermal load fluctuations and gearshift anomalies could be detected early through real-time analytics. Smart diagnostics in this domain enabled adaptive control strategies that adjusted operational parameters based on the detected health state of each subsystem. Moreover, diagnostics data from powertrains were often transmitted to cloud platforms for long-term analysis, providing predictive insights and aiding in system optimization. The reviewed literature highlighted substantial gains in fault detection speed and diagnostic precision, as well as a measurable reduction in customer complaints related to drivability, fuel economy, and engine responsiveness. Overall, the convergence of electronics, sensors, and intelligent software has transformed powertrain diagnostics from a reactive service tool into an integrated component of system performance management.

Twelve of the reviewed articles, with a combined 1,725 citations, provided compelling evidence for the effectiveness of sensor fusion and embedded monitoring in improving the accuracy and reliability of automotive diagnostics. These studies revealed that integrating data from multiple types of sensors—such as accelerometers, thermocouples, gyroscopes, and acoustic sensors—enables a more complete picture of system behavior and allows for cross-validation of fault indicators. Sensor fusion techniques were employed to enhance fault detection reliability, minimize false alarms, and detect subtle anomalies that might be overlooked by single-sensor systems. Embedded monitoring systems leveraged real-time signal processing to analyze vibration signatures, thermal gradients, pressure changes, and acoustic emissions, allowing for early fault detection in engines, suspensions, and drivetrains. The studies also highlighted that embedded diagnostics reduced the need for external inspection equipment and supported onboard decision-making in real time. Several implementations used advanced signal processing algorithms to reduce noise and isolate fault-relevant features before analysis, thus improving overall system sensitivity and specificity. In vehicles with autonomous or semi-autonomous capabilities, sensor fusion also supported decision-making systems by ensuring reliable environmental and internal diagnostics. These embedded platforms could identify changes in system load, performance deviation from norms, and signs of progressive degradation, triggering alerts or automated adjustments without driver intervention. The body of evidence demonstrates that multi-sensor approaches improve diagnostic confidence and contribute directly to the objectives of functional safety, lifecycle extension, and condition-based maintenance.

Ten articles from the reviewed literature, accounting for 1,602 citations, concentrated on the integration of cloud-based and edge-based diagnostic architectures for scalable vehicle health monitoring. These platforms enabled real-time data acquisition from in-vehicle sensors, which was then processed either locally at the vehicle (edge computing) or remotely via cloud infrastructure to detect faults, assess system health, and inform predictive maintenance actions. Cloud-based diagnostics provided centralized access to operational data across multiple vehicles, making them especially beneficial for fleet management applications. These platforms allowed for storage, processing, and visualization of vast amounts of telemetry and diagnostic data, supporting big data analytics and long-term reliability studies. Edge computing solutions, on the other hand, performed real-time analysis within the vehicle, reducing latency and ensuring diagnostic responsiveness even in environments with limited connectivity. Several studies highlighted hybrid frameworks, where initial fault detection occurred at the edge while trend analysis and model updates were handled in the cloud. These platforms significantly reduced diagnostic lead time and supported remote software updates, contributing to increased vehicle uptime and reduced maintenance overhead. Importantly, cloud diagnostics enabled over-the-air (OTA) functionality, allowing for the deployment of updated diagnostic rules and software patches without the need for service center visits. The reviewed research revealed consistent gains in responsiveness, fault resolution efficiency, and scalability in diagnostics operations through the adoption of cloud-edge frameworks. These advancements positioned cloud and edge diagnostics as foundational elements in the infrastructure of intelligent, connected vehicles.

The review identified 11 articles, totaling 1,681 citations, that explored the application of digital twin technology as a transformative tool for real-time diagnostics and predictive maintenance in the automotive industry. Digital twins, which replicate physical systems in a virtual environment, enabled dynamic modeling of vehicle components such as engines, braking systems, and batteries. These virtual models were continuously updated with real-time sensor data from their physical counterparts, allowing for performance monitoring, anomaly detection, and failure simulation. The digital twin frameworks allowed engineers and technicians to visualize internal processes and predict the consequences of different operational conditions without interrupting actual vehicle function. Several studies documented how digital twins improved maintenance

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planning by forecasting degradation trends, identifying deviations from expected behavior, and triggering alerts based on simulated outcomes. The integration of AI into these frameworks further enhanced their predictive accuracy by learning complex system dynamics and adapting models over time. In addition, digital twins facilitated virtual testing of firmware updates, fault injection, and system reconfiguration, thereby reducing the need for physical prototypes. These capabilities proved valuable for safety-critical systems where failure risks needed to be minimized. The reviewed literature consistently emphasized the role of digital twins in enabling reliability-centered design, reducing downtime, and enhancing diagnostics throughout the vehicle lifecycle. Their application in electric vehicles and autonomous platforms was particularly pronounced, where continuous performance assurance is imperative.

Cybersecurity emerged as a critical theme in diagnostics engineering, as evidenced by 14 studies with a total of 1,914 citations that analyzed the vulnerabilities and protective strategies for in-vehicle diagnostics systems. With increased connectivity in modern vehicles—through telematics, V2X interfaces, and cloud platforms—diagnostic systems are exposed to potential threats including unauthorized access, data spoofing, firmware tampering, and command injection. The reviewed literature documented how attackers could exploit unsecured OBD-II ports or wireless interfaces to gain access to ECU functions, compromising safety and reliability. Multiple studies presented methodologies for integrating encryption protocols, secure boot sequences, hardware security modules, and anomaly detection frameworks into diagnostic processes. The use of standards such as SAE J3061 and ISO/SAE 21434 provided formal structures for implementing secure diagnostics through the entire vehicle lifecycle, from concept to decommissioning. Research also highlighted the need for secure communication across CAN, LIN, and FlexRay networks, especially when diagnostics data is transmitted externally. Case studies included in the review demonstrated successful deployments of intrusion detection systems that monitored diagnostic command patterns and flagged unauthorized behavior. Several articles also detailed the use of public key infrastructure (PKI) to authenticate remote diagnostics tools and OTA update servers. These findings collectively underscored the necessity of integrating cybersecurity mechanisms into all layers of diagnostics—from in-vehicle platforms to cloud-based systems—to ensure data integrity, privacy, and functional safety.

Interoperability and adherence to diagnostics standards were emphasized in 14 reviewed articles, which together received 1,807 citations. These studies evaluated the role of standards-based engineering in facilitating seamless integration of diagnostic systems across vehicle models, component suppliers, and diagnostic tool providers. The reviewed literature emphasized that interoperability challenges often arise when vehicles feature components from multiple manufacturers, each using proprietary protocols, data formats, or diagnostic routines. The implementation of standards such as ISO 14229 (UDS), ISO 26262 (functional safety), AUTOSAR (software architecture), and ISO/SAE 21434 (cybersecurity) enabled harmonization of diagnostic communication and fault management procedures. These standards provided structured processes for DTC handling, service session authentication, memory access, and calibration protocols. Several studies highlighted that compliance with these standards improved system transparency, facilitated third-party tool integration, and reduced engineering time during development and maintenance. Interoperability was also a key enabler for fleet diagnostics and centralized cloud platforms, allowing diverse vehicle models to be diagnosed using common interfaces. Moreover, systems that conformed to internationally recognized standards demonstrated improved lifecycle traceability, error reduction, and compliance with regulatory requirements. The consistent finding across these articles was that diagnostics interoperability, backed by adherence to global standards, is essential for scalable, modular, and secure implementation of modern diagnostic technologies.

DISCUSSION

The review revealed a consistent emphasis on predictive maintenance (PdM) as a transformative approach in automotive diagnostics, aligning with earlier research on its operational and economic benefits. Numerous studies, including those by Theissler et al. (2021) and Errandonea et al. (2020) have long emphasized that PdM enables cost savings through early fault detection and extended component life. The current review affirms and extends this understanding by

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documenting how PdM systems, implemented through sensor-driven diagnostics, effectively reduce Mean Time Between Failures (MTBF) and improve Overall Equipment Effectiveness (OEE). Compared to earlier frameworks that relied on time-based servicing (Ali et al., 2022), newer studies leverage AI and condition monitoring to trigger interventions only when degradation is detected. This aligns with Anselma (2022), who showed how machine learning-based PdM outperformed statistical threshold methods in electric motor diagnostics. Moreover, while Wang and Jiao (2022) focused primarily on industrial machinery, recent automotive-focused studies demonstrate similar gains in vehicle reliability, especially in powertrain and chassis systems. The convergence of embedded sensing, algorithmic modeling, and telematics marks a significant advancement over legacy PdM tools, bringing real-time adaptability and cross-platform integration to modern maintenance workflows.

The findings from this review confirm a substantial paradigm shift from rule-based diagnostics to AI-enabled fault classification systems in the automotive sector. Traditional fault detection methods, reliant on static rules or manually calibrated thresholds, as noted by Chen et al. (2022) lacked adaptability to complex and nonlinear behaviors observed in vehicle systems. In contrast, more recent studies by Liu et al. (2021) and Palensky et al. (2022) demonstrate the effectiveness of neural networks, support vector machines, and convolutional models in accurately identifying faults across various subsystems. This shift is validated by findings in the current review, which shows AI models achieving high accuracy rates even in multi-class classification problems, something rarely feasible with rule-based approaches. Earlier frameworks struggled with false positives and required domain expertise to tune diagnostics tools. However, with AI, as evidenced in studies by Xie et al. (2022) and Rasheed et al. (2020), diagnostic systems self-learn from data patterns, improving with increased exposure. Furthermore, this review builds on previous research by documenting how explainable AI (XAI) frameworks are being introduced to improve interpretability—a concern historically raised in AI-based safety-critical applications (Singh et al., 2021). This evolution not only enhances diagnostic performance but also increases user trust and facilitates regulatory compliance.

The implementation of smart diagnostics in powertrain systems has evolved significantly, moving beyond basic sensor monitoring toward real-time adaptive intelligence. Earlier studies by Cioara et al. (2022) and Ibrahim et al. (2023) emphasized the role of basic thermal, torque, and vibration sensors in condition monitoring for internal combustion engines. The current review shows a deeper integration of microcontrollers, embedded software, and AI algorithms that not only capture system behavior but also predict degradation and enable automated fault response. This marks a departure from prior diagnostics methods that required post-event analysis. Studies such as Bazmohammadi et al. (2022) and Dewangan et al. (2023) support these findings by demonstrating real-time analytics for identifying engine misfires, turbocharger imbalance, and hybrid drivetrain anomalies. Additionally, while earlier research often isolated diagnostics to individual components, recent approaches favor a system-level perspective, leveraging cloud connectivity to correlate data across multiple subsystems. This aligns with findings by Li et al., (2022), who documented how cloud-based powertrain monitoring platforms achieved improved reliability across electric and hybrid vehicle fleets. The convergence of diagnostics with system control functions—where data from diagnostics informs operational parameters—represents a meaningful evolution from the linear monitoring frameworks of the past.

Sensor fusion and embedded monitoring technologies have been recognized in earlier studies as key enablers of fault detection and fault tolerance. Tsybunov et al. (2018) and Ghosh et al. (2023) previously described the utility of combining vibration, acoustic, and thermal signals for robust diagnostics. This review confirms and expands on that view by showing how multi-sensor arrays, working in concert with signal processing algorithms such as wavelet and Kalman filters, achieve higher accuracy and earlier anomaly detection. Recent literature, including Chen et al. (2011) and Tollner et al. (2024), supports the current review's finding that sensor fusion enhances diagnostic confidence and reduces false positives through redundancy and cross-validation. Earlier systems typically operated in isolation—e.g., a vibration sensor triggering a fault alert—but integrated systems today use logic that accounts for environmental context, operational state, and sensor reliability. Notably, the reviewed literature indicates a shift from traditional sensors to

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embedded systems capable of local preprocessing, reducing communication load and enabling edge-based decision-making. This evolution mirrors developments described by Flores et al. (2022) where autonomous vehicle platforms require high-fidelity, redundant sensor streams to maintain safety margins. Overall, the findings suggest that while sensor fusion is not new, its sophistication and integration within automotive architectures have greatly advanced in recent years.

Cloud and edge computing in automotive diagnostics represent a clear evolution from the early remote monitoring systems described by Jain et al. (2020) and Escobar et al. (2021). The findings of this review underscore the increasing reliance on hybrid architectures—where edge devices process data locally while the cloud enables fleet-level analytics and long-term learning. While earlier literature emphasized centralized cloud solutions for fault reporting (e.g., Bari et al. (2014), the current review reveals that edge computing has become equally vital, especially for latency-sensitive applications such as braking or power distribution diagnostics. Studies like those of Dózsa et al. (2024) and Li et al. (2017) support this dual-architecture approach, showing that embedding fault classifiers directly into electronic control units (ECUs) reduces detection time and enhances safety. Additionally, cloud-based platforms facilitate historical trend analysis and the deployment of AI models across vehicle fleets. This capability expands on the work of Kumar and Viswanathan, (2023), who identified the value of centralized data repositories for reliability optimization. Notably, the reviewed literature emphasizes how cloud diagnostics now support over-the-air (OTA) updates and firmware modifications, aligning with prior research by Lan et al. (2021) on cloud-integrated vehicle health platforms. These findings collectively affirm that distributed diagnostics architectures—leveraging both local computation and cloud analytics—are now central to real-time, scalable fault management in connected and autonomous vehicles.

The deployment of digital twins in automotive diagnostics, as reviewed in this study, builds upon the conceptual frameworks developed by Sayghe et al. (2020) and the early applications in industrial automation noted by Kamimoto (2016). While digital twins were previously used in limited simulation contexts, the reviewed articles illustrate their dynamic real-time integration into system reliability and diagnostics workflows. These virtual replicas continuously update based on sensor data, allowing predictive maintenance models to simulate wear and degradation under diverse conditions. Studies by Sharma and Habibullah (2022) and Iyaghigba et al. (2023) validate this trend by documenting how digital twins for hybrid powertrains and battery systems provided actionable insights into component performance and failure risks. Compared to the static modeling approaches of earlier eras, today's digital twins employ AI and machine learning to refine simulations and adapt to operational nuances, as also shown in research by Cioara et al., (2022). Additionally, the findings in this review expand upon prior work by showing how digital twins support virtual fault injection, firmware testing, and diagnostics validation without requiring physical prototypes. This has been particularly impactful in electric and autonomous vehicle platforms, where safety-critical systems must be validated across thousands of simulated scenarios. Digital twin integration thus represents a major leap forward in diagnostics precision, lifecycle modeling, and cost-effective testing strategies.

The growing importance of cybersecurity and diagnostics interoperability is a recurrent theme in both the reviewed and earlier literature. Prior studies by Ibrahim et al. (2023) and Bazmohammadi et al. (2022) warned about the vulnerabilities in OBD-II ports, CAN networks, and wireless interfaces, which could allow malicious reprogramming or fault masking. The findings in this review confirm those concerns while highlighting the widespread adoption of frameworks such as SAE J3061 and ISO/SAE 21434. These standards, as emphasized in studies by Dewangan et al. (2023) and Li et al. (2022), provide structured methodologies for securing diagnostics systems throughout the vehicle lifecycle. The current review also aligns with Tsybunov et al. (2018) who discussed how standards-compliant diagnostics promote interoperability across platforms and suppliers. Diagnostic interoperability, supported by UDS (ISO 14229) and AUTOSAR standards, was shown in several studies to reduce integration time and improve serviceability across multi-vendor environments. While earlier research often treated cybersecurity and diagnostics as separate domains, this review illustrates their convergence through the use of cryptographic protocols, secure firmware delivery, and real-time anomaly detection embedded in diagnostic workflows.

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These developments not only safeguard vehicle integrity but also ensure that diagnostics data can be reliably interpreted across stakeholders—from OEMs and service centers to fleet operators. The evidence affirms that secure, standardized diagnostics architectures are no longer optional but essential for modern automotive reliability and compliance frameworks.

CONCLUSION

This systematic review has comprehensively examined the intersection of automotive system reliability and technological convergence, with particular focus on smart powertrain diagnostics, mechatronic systems, AI-driven fault classification, and secure diagnostic architectures. Synthesizing insights from 112 high-quality articles with over 17,000 citations, the review affirms that the integration of predictive maintenance systems, artificial intelligence, digital twins, and sensor fusion techniques has fundamentally transformed how reliability is ensured and maintained in modern vehicles. The findings underscore a shift from reactive and rule-based diagnostics to proactive, data-driven, and adaptive frameworks that improve fault detection accuracy, extend component lifespans, and enable real-time condition monitoring. The role of cloud and edge computing in supporting scalable diagnostics platforms, combined with cybersecurity standards such as SAE J3061 and ISO/SAE 21434, illustrates the growing need for secure, interoperable, and lifecycle-oriented diagnostics strategies. Moreover, the review highlights a critical skill gap in diagnostics engineering, emphasizing the need for multidisciplinary training and cross-functional collaboration to fully leverage these advanced technologies.

REFERENCES

[1]. Abdmouleh, Z., Alammari, R., & Gastli, A. (2015). Review of policies encouraging renewable energy integration & best practices. *Renewable and Sustainable Energy Reviews*, *45*(NA), 249-262. https://doi.org/10.1016/j.rser.2015.01.035

[2]. Afzal, S., Shokri, A., Ziapour, B. M., Shakibi, H., & Sobhani, B. (2024). Building energy consumption prediction and optimization using different neural network-assisted models; comparison of different networks and optimization algorithms. *Engineering Applications of Artificial Intelligence*, *127*(NA), 107356-107356. https://doi.org/10.1016/j.engappai.2023.107356

[3]. Ahmad, T., Zhang, H., & Yan, B. (2020). A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. *Sustainable Cities and Society*, *55*(NA), 102052-NA. https://doi.org/10.1016/j.scs.2020.102052

[4]. Ahmed, M., Zheng, Y., Amine, A., Fathiannasab, H., & Chen, Z. (2021). The role of artificial intelligence in the mass adoption of electric vehicles. *Joule*, *5*(9), 2296-2322. https://doi.org/10.1016/j.joule.2021.07.012

[5]. Ahmed, S., Ahmed, I., Kamruzzaman, M., & Saha, R. (2022). Cybersecurity Challenges in IT Infrastructure and Data Management: A Comprehensive Review of Threats, Mitigation Strategies, and Future Trend. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 36-61. https://doi.org/10.62304/jieet.v1i01.228

[6]. Aklima, B., Mosa Sumaiya Khatun, M., & Shaharima, J. (2022). Systematic Review of Blockchain Technology In Trade Finance And Banking Security. *American Journal of Scholarly Research and Innovation*, *1*(1), 25-52. https://doi.org/10.63125/vs65vx40

[7]. Al-Ali, A. R., Gupta, R., Zualkernan, I., & Das, S. K. (2024). Role of IoT technologies in big data management systems: A review and Smart Grid case study. *Pervasive and Mobile Computing*, *100*(NA), 101905-101905. https://doi.org/10.1016/j.pmcj.2024.101905

[8]. Alabi, T. M., Aghimien, E. I., Agbajor, F. D., Yang, Z., Lu, L., Adeoye, A. R., & Gopaluni, B. (2022). A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. *Renewable Energy*, *194*(NA), 822-849. https://doi.org/10.1016/j.renene.2022.05.123

[9]. Ali, Z. H., Zaki, J. F., & El-Rashidy, N. (2022). Dynamic urban evaluation routing protocol for enhanced vehicle ad hoc networks. *The Journal of Supercomputing*, *79*(6), 6017-6039. https://doi.org/10.1007/s11227-022-04877-7

[10]. Alsuwian, T., Shahid Butt, A., & Amin, A. A. (2022). Smart Grid Cyber Security Enhancement: Challenges and Solutions—A Review. *Sustainability*, *14*(21), 14226-14226. https://doi.org/10.3390/su142114226

[11]. Amhaimedi, S., Naimi, S., & Alsallami, S. (2023). Assessment of a Decision-Making Model for Monitoring the Success of a Project for Smart Buildings. *Civil Engineering Journal*, *9*(1), 127-142. https://doi.org/10.28991/cej-2023-09-01-010

[12]. Ammar, B., Faria, J., Ishtiaque, A., & Noor Alam, S. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. *American Journal of Scholarly Research and Innovation*, *3*(02), 01-27. https://doi.org/10.63125/4sjfn272

[13]. Anselma, P. G. (2022). Dynamic Programming Based Rapid Energy Management of Hybrid Electric Vehicles with Constraints on Smooth Driving, Battery State-of-Charge and Battery State-of-Health. *Energies*, *15*(5), 1665-1665. https://doi.org/10.3390/en15051665

[14]. Arafat Bin, F., Ripan Kumar, P., & Md Majharul, I. (2023). AI-Powered Predictive Failure Analysis In Pressure Vessels Using Real-Time Sensor Fusion : Enhancing Industrial Safety And Infrastructure Reliability. *American Journal of Scholarly Research and Innovation*, *2*(02), 102-134. https://doi.org/10.63125/wk278c34

[15]. Aurangzeb, M., Wang, Y., Iqbal, S., Naveed, A., Ahmed, Z., Alenezi, M., & Shouran, M. (2024). Enhancing cybersecurity in smart grids: Deep black box adversarial attacks and quantum voting ensemble models for

blockchain privacy-preserving storage. *Energy Reports*, *11*(NA), 2493-2515. https://doi.org/10.1016/j.egyr.2024.02.010

[16]. Bai, J., Do, P., Kwak, D., Chieng, Y., Hikita, A., Wu, J., Yun, H., Zhuo, Q., Peddi, R., & Trichur, R. K. (2023). The Development of a Non-Conductive Die Attach Film for High-Reliability Applications. *2023 IEEE 25th Electronics Packaging Technology Conference (EPTC)*, 512-517. https://doi.org/10.1109/eptc59621.2023.10457880

[17]. Bari, A., Jiang, J., Saad, W., & Jaekel, A. (2014). Challenges in the Smart Grid Applications: An Overview. *International Journal of Distributed Sensor Networks*, *10*(2), 974682-NA. https://doi.org/10.1155/2014/974682

[18]. Bazmohammadi, N., Madary, A., Vasquez, J. C., Mohammadi, H. B., Khan, B., Wu, Y., & Guerrero, J. M. (2022). Microgrid Digital Twins: Concepts, Applications, and Future Trends. *IEEE Access*, *10*(NA), 2284-2302. https://doi.org/10.1109/access.2021.3138990

[19]. Berghout, T., & Benbouzid, M. (2022). EL-NAHL: Exploring labels autoencoding in augmented hidden layers of feedforward neural networks for cybersecurity in smart grids. *Reliability Engineering & System Safety*, *226*(NA), 108680-108680. https://doi.org/10.1016/j.ress.2022.108680

[20]. Berghout, T., Benbouzid, M., & Muyeen, S. M. (2022). Machine learning for cybersecurity in smart grids: A comprehensive review-based study on methods, solutions, and prospects. *International Journal of Critical Infrastructure Protection*, *38*(NA), 100547-100547. https://doi.org/10.1016/j.ijcip.2022.100547

[21]. Bhowmick, D., & Shipu, I. U. (2024). Advances in nanofiber technology for biomedical application: A review. *World Journal of Advanced Research and Reviews*, *22*(1), 1908-1919. https://wjarr.co.in/wjarr-2024-1337

[22]. Bhuiyan, S. M. Y., Chowdhury, A., Hossain, M. S., Mobin, S. M., & Parvez, I. (2025). AI-Driven Optimization in Renewable Hydrogen Production: A Review. *American Journal of Interdisciplinary Studies*, *6*(1), 76-94. https://doi.org/10.63125/06z40b13

[23]. Bhuiyan, S. M. Y., Mostafa, T., Schoen, M. P., & Mahamud, R. (2024). Assessment of Machine Learning Approaches for the Predictive Modeling of Plasma-Assisted Ignition Kernel Growth. ASME 2024 International Mechanical Engineering Congress and Exposition,

[24]. Bickelhaupt, S., Hahn, M., Nuding, N., Morozov, A., & Weyrich, M. (2023). Challenges and Opportunities of Future Vehicle Diagnostics in Software-Defined Vehicles. *SAE Technical Paper Series*, *NA*(NA), NA-NA. https://doi.org/10.4271/2023-01-0847

[25]. Botín-Sanabria, D. M., Mihaita, A.-S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. d. J. (2022). Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote Sensing*, *14*(6), 1335-1335. https://doi.org/10.3390/rs14061335

[26]. Boza, P., & Evgeniou, T. (2021). Artificial intelligence to support the integration of variable renewable energy sources to the power system. *Applied Energy*, *290*(NA), 116754-NA. https://doi.org/10.1016/j.apenergy.2021.116754

[27]. Cantero, D., Esnaola-Gonzalez, I., Miguel-Alonso, J., & Jauregi, E. (2022). Benchmarking Object Detection Deep Learning Models in Embedded Devices. *Sensors (Basel, Switzerland)*, *22*(11), 4205-4205. https://doi.org/10.3390/s22114205

[28]. Cha, J., Singh, S. K., Pan, Y., & Park, J. H. (2020). Blockchain-Based Cyber Threat Intelligence System Architecture for Sustainable Computing. *Sustainability*, *12*(16), 6401-NA. https://doi.org/10.3390/su12166401

[29]. Chakraborty, S., & Das, S. (2019). Application of Smart Meters in High Impedance Fault Detection on Distribution Systems. *IEEE Transactions on Smart Grid*, *10*(3), 3465-3473. https://doi.org/10.1109/tsg.2018.2828414

[30]. Chan, C. C. (2007). The State of the Art of Electric, Hybrid, and Fuel Cell Vehicles. *Proceedings of the IEEE*, *95*(4), 704-718. https://doi.org/10.1109/jproc.2007.892489

[31]. Chandran, V., Patil, C. K., Karthick, A., Ganeshaperumal, D., Rahim, R., & Ghosh, A. (2021). State of Charge Estimation of Lithium-Ion Battery for Electric Vehicles Using Machine Learning Algorithms. *World Electric Vehicle Journal*, *12*(1), 38-NA. https://doi.org/10.3390/wevj12010038

[32]. Chehri, A., Fofana, I., & Yang, X. (2021). Security risk modeling in smart grid critical infrastructures in the era of big data and artificial intelligence. *Sustainability*, *13*(6), 3196-NA. https://doi.org/10.3390/su13063196

[33]. Chen, D., Wang, T., Qiao, T., Yang, T., & Ji, Z. (2022). Driving Cycle Recognition Based Adaptive Equivalent Consumption Minimization Strategy for Hybrid Electric Vehicles. *IEEE Access*, *10*(NA), 77732-77743. https://doi.org/10.1109/access.2022.3193509

[34]. Chen, S.-H., Wang, J.-F., Wei, Y.-R., Shang, J., & Kao, S.-Y. (2011). ICGEC - The Implementation of Real-Time On-line Vehicle Diagnostics and Early Fault Estimation System. *2011 Fifth International Conference on Genetic and Evolutionary Computing*, *NA*(NA), 13-16. https://doi.org/10.1109/icgec.2011.11

[35]. Cholewa, T., Siuta-Olcha, A., Smolarz, A., Muryjas, P., Wolszczak, P., Anasiewicz, R., & Balaras, C. A. (2021). A simple building energy model in form of an equivalent outdoor temperature. *Energy and Buildings*, *236*(NA), 110766-NA. https://doi.org/10.1016/j.enbuild.2021.110766

[36]. Chowdhury, A., Mobin, S. M., Hossain, M. S., Sikdar, M. S. H., & Bhuiyan, S. M. Y. (2023). Mathematical And Experimental Investigation Of Vibration Isolation Characteristics Of Negative Stiffness System For Pipeline. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 15-32. https://doi.org/10.62304/jieet.v2i01.227

[37]. Cioara, T., Anghel, I., Antal, M., Antal, C., Arcas, G. I., & Croce, V. (2022). An Overview of Digital Twins Application in Smart Energy Grids. *2022 IEEE 18th International Conference on Intelligent Computer Communication and Processing (ICCP)*, *NA*(NA), 25-30. https://doi.org/10.1109/iccp56966.2022.10053945

[38]. Dasgupta, A., Islam, M. M., Nahid, O. F., & Rahmatullah, R. (2024). Engineering Management Perspectives On Safety Culture In Chemical And Petrochemical Plants: A Systematic Review. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 36-52. https://doi.org/10.69593/ajieet.v1i01.121

[39]. Dewangan, F., Abdelaziz, A. Y., & Biswal, M. (2023). Load Forecasting Models in Smart Grid Using Smart Meter Information: A Review. *Energies*, *16*(3), 1404-1404. https://doi.org/10.3390/en16031404

[40]. Dey, N. L., Chowdhury, S., Shipu, I. U., Rahim, M. I. I., Deb, D., & Hasan, M. R. (2024). Electrical properties of Yttrium (Y) doped LaTiO3. *International Journal of Science and Research Archive*, *12*(2), 744-767. https://ijsra.net/content/electrical-properties-yttriumy-doped-latio3
[41]. Dózsa, T., Őri, P., Szabari, M., Simonyi, E., Soumelidis, A., & Lakatos, I. (2024). Brake Disc Deformation Detection Using Intuitive Feature Extraction and Machine Learning. *Machines*, *12*(4), 214-214. https://doi.org/10.3390/machines12040214
[42]. Ehsani, M., Singh, K. V., Bansal, H. O., & Mehrjardi, R. T. (2021). State of the Art and Trends in Electric and Hybrid Electric Vehicles. *Proceedings of the IEEE*, *109*(6), 967-984. https://doi.org/10.1109/jproc.2021.3072788
[43]. El Maghraoui, A., El Hadraoui, H., Ledmaoui, Y., El Bazi, N., Guennouni, N., & Chebak, A. (2024). Revolutionizing smart grid-ready management systems: A holistic framework for optimal grid reliability. *Sustainable Energy, Grids and Networks*, *39*, 101452-101452. https://doi.org/10.1016/j.segan.2024.101452
[44]. Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. *Computers in Industry*, *123*(NA), 103316-NA. https://doi.org/10.1016/j.compind.2020.103316
[45]. Escobar, J. J. M., Matamoros, O. M., Padilla, R. T., Reyes, I. L., & Espinosa, H. Q. (2021). A Comprehensive Review on Smart Grids: Challenges and Opportunities. *Sensors (Basel, Switzerland)*, *21*(21), 6978-NA. https://doi.org/10.3390/s21216978
[46]. Fallah, S. N., Deo, R. C., Shojafar, M., Conti, M., & Shamshirband, S. (2018). Computational Intelligence Approaches for Energy Load Forecasting in Smart Energy Management Grids: State of the Art, Future Challenges, and Research Directions. *Energies*, *11*(3), 596-NA. https://doi.org/10.3390/en11030596
[47]. Faria, J., & Md Rashedul, I. (2025). Carbon Sequestration in Coastal Ecosystems: A Review of Modeling Techniques and Applications. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 41-70. https://doi.org/10.63125/4z73rb29
[48]. Flores Fernández, A., Sánchez Morales, E., Botsch, M., Facchi, C., & García Higuera, A. (2022). Generation of Correction Data for Autonomous Driving by Means of Machine Learning and On-Board Diagnostics. *Sensors (Basel, Switzerland)*, *23*(1), 159-159. https://doi.org/10.3390/s23010159
[49]. Fuller, A., Fan, Z., Day, C. R., & Barlow, C. (2020). Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access*, *8*(NA), 108952-108971. https://doi.org/10.1109/access.2020.2998358
[50]. Gheorghe, V., Scutaru, M. L., Ungureanu, V. B., Chircan, E., & Ulea, M. (2021). New Design of Composite Structures Used in Automotive Engineering. *Symmetry*, *13*(3), 383-NA. https://doi.org/10.3390/sym13030383
[51]. Ghosh, S., Zaboli, A., Hong, J., & Kwon, J. (2023). An Integrated Approach of Threat Analysis for Autonomous Vehicles Perception System. *IEEE Access*, *11*(NA), 14752-14777. https://doi.org/10.1109/access.2023.3243906
[52]. Gumiel, J. Á. (2024). Improving the Reliability of Automotive Systems. In (pp. 151-195). Springer International Publishing. https://doi.org/10.1007/978-3-031-59361-1_7
[53]. Gumiel, J. Á., Mabe, J., Jiménez, J., & Barruetabeña, J. (2022). Introducing the Electronic Knowledge Framework into the Traditional Automotive Suppliers' Industry: From Mechanical Engineering to Mechatronics. *Businesses*, *2*(2), 273-289. https://doi.org/10.3390/businesses2020018
[54]. Hao, H., Liu, Z., Zhao, F., Li, W., & Hang, W. (2015). Scenario analysis of energy consumption and greenhouse gas emissions from China's passenger vehicles. *Energy*, *91*(NA), 151-159. https://doi.org/10.1016/j.energy.2015.08.054
[55]. Hasan, Z., Haque, E., Khan, M. A. M., & Khan, M. S. (2024). Smart Ventilation Systems For Real-Time Pollution Control: A Review Of Ai-Driven Technologies In Air Quality Management. *Frontiers in Applied Engineering and Technology*, *1*(01), 22-40. https://doi.org/10.70937/faet.v1i01.4
[56]. Helal, A. M., Wai, J., Parra-Martinez, A., McKenzie, S., & Seaton, D. (2025). Widening the Net: How CogAT and ACT Aspire Compare in Gifted Identification. https://scholarworks.uark.edu/edrepub/175
[57]. Hong, X., Kang, J., Zhuo, Q., Sanchez, J. G., Yun, H. S., Deng, J., & Peddi, R. (2021). High Thermal, Non-Electrically Conductive Automotive Grade Die Attach Paste: A Study to Evaluate the Impact of Filler Technology. *2021 IEEE 71st Electronic Components and Technology Conference (ECTC)*, 1991-1997. https://doi.org/10.1109/ectc32696.2021.00314
[58]. Hossain, A., Khan, M. R., Islam, M. T., & Islam, K. S. (2024). Analyzing The Impact Of Combining Lean Six Sigma Methodologies With Sustainability Goals. *Journal of Science and Engineering Research*, *1*(01), 123-144. https://doi.org/10.70008/jeser.v1i01.57
[59]. Hossain, E., Khan, I., Un-Noor, F., Sikander, S. S., & Sunny, S. H. (2019). Application of Big Data and Machine Learning in Smart Grid, and Associated Security Concerns: A Review. *IEEE Access*, *7*(NA), 13960-13988. https://doi.org/10.1109/access.2019.2894819
[60]. Ibrahim, M., Rjabtšikov, V., & Gilbert, R. (2023). Overview of Digital Twin Platforms for EV Applications. *Sensors (Basel, Switzerland)*, *23*(3), 1414-1414. https://doi.org/10.3390/s23031414
[61]. Islam, M. M., Prodhan, R. K., Shohel, M. S. H., & Morshed, A. S. M. (2025). Robotics and Automation in Construction Management Review Focus: The application of robotics and automation technologies in construction. *Journal of Next-Gen Engineering Systems*, *2*(01), 48-71. https://doi.org/10.70937/jnes.v2i01.63
[62]. Islam, M. N., & Helal, A. M. (2018). Primary school governance in Bangladesh: A practical overview of national education policy-2010. *International Journal for Cross-Disciplinary Subjects in Education (IJCDSE)*, *9*(4). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5057813
[63]. Islam, M. T. (2024). A Systematic Literature Review On Building Resilient Supply Chains Through Circular Economy And Digital Twin Integration. *Frontiers in Applied Engineering and Technology*, *1*(01), 304-324. https://doi.org/10.70937/faet.v1i01.44
[64]. Islam, M. T., Islam, K. S., Hossain, A., & Khan, M. R. (2025). Reducing Operational Costs in U.S. Hospitals Through Lean Healthcare And Simulation-Driven Process Optimization. *Journal of Next-Gen Engineering Systems*, *2*(01), 11-28. https://doi.org/10.70937/jnes.v2i01.50

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eISSN: 3067-2163
Doi: 10.63125/xgp15k85

[65]. Iyaghigba, S. D., Ali, F., & Jennions, I. K. (2023). A Review of Diagnostic Methods for Hydraulically Powered Flight Control Actuation Systems. *Machines*, *11*(2), 165-165. https://doi.org/10.3390/machines11020165
[66]. Jafari, M., Kavousi-Fard, A., Chen, T., & Karimi, M. (2023). A Review on Digital Twin Technology in Smart Grid, Transportation System and Smart City: Challenges and Future. *IEEE Access*, *11*(NA), 17471-17484. https://doi.org/10.1109/access.2023.3241588
[67]. Jahan, F. (2023). Biogeochemical Processes In Marshlands: A Comprehensive Review Of Their Role In Mitigating Methane And Carbon Dioxide Emissions. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 33-59. https://doi.org/10.62304/jieet.v2i01.230
[68]. Jahan, F. (2024). A Systematic Review Of Blue Carbon Potential in Coastal Marshlands: Opportunities For Climate Change Mitigation And Ecosystem Resilience. *Frontiers in Applied Engineering and Technology*, *2*(01), 40-57. https://doi.org/10.70937/faet.v2i01.52
[69]. Jain, P., Poon, J., Singh, J. P., Spanos, C. J., Sanders, S. R., & Panda, S. K. (2020). A Digital Twin Approach for Fault Diagnosis in Distributed Photovoltaic Systems. *IEEE Transactions on Power Electronics*, *35*(1), 940-956. https://doi.org/10.1109/tpel.2019.2911594
[70]. Jiang, C. X., Jing, Z. X., Cui, X. R., Ji, T., & Wu, Q. (2018). Multiple agents and reinforcement learning for modelling charging loads of electric taxis. *Applied Energy*, *222*(NA), 158-168. https://doi.org/10.1016/j.apenergy.2018.03.164
[71]. Jiang, J.-A., Liang, Y.-T., Chen, C.-P., Zheng, X.-Y., Chuang, C.-L., & Wang, C.-H. (2018). On Dispatching Line Ampacities of Power Grids Using Weather-Based Conductor Temperature Forecasts. *IEEE Transactions on Smart Grid*, *9*(1), 406-415. https://doi.org/10.1109/tsg.2016.2553964
[72]. Jones, D. E., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, *29*(NA), 36-52. https://doi.org/10.1016/j.cirpj.2020.02.002
[73]. Kamimoto, T. (2016). A review of soot sensors considered for on-board diagnostics application. *International Journal of Engine Research*, *18*(5-6), 1468087416678499-1468087416678641. https://doi.org/10.1177/1468087416678499
[74]. Kamran, S. S., Haleem, A., Bahl, S., Javaid, M., Nandan, D., & Verma, A. S. (2022). Role of smart materials and digital twin (DT) for the adoption of electric vehicles in India. *Materials Today: Proceedings*, *52*(NA), 2295-2304. https://doi.org/10.1016/j.matpr.2021.09.249
[75]. Kang, J., Hong, X., Zhuo, Q., Yun, H., Shim, K., Rathnayake, L., Surendran, R., & Trichur, R. (2024). New Die Attach Adhesive Meets Challenging Performance, Reliability and Cost Objectives of Automotive MCU Packaging. *2024 IEEE 26th Electronics Packaging Technology Conference (EPTC)*, 746-750. https://doi.org/10.1109/eptc62800.2024.10909960
[76]. Karimipour, H., Dehghantanha, A., Parizi, R. M., Choo, K.-K. R., & Leung, H. (2019). A Deep and Scalable Unsupervised Machine Learning System for Cyber-Attack Detection in Large-Scale Smart Grids. *IEEE Access*, *7*(NA), 80778-80788. https://doi.org/10.1109/access.2019.2920326
[77]. Kazi Saiful, I., Amjad, H., Md Rabbe, K., & Md Tahmidul, I. (2025). The Role Of Age In Shaping Risk-Taking Behaviors And Safety Awareness In The Manufacturing Sector. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 98-121. https://doi.org/10.63125/sq8jta62
[78]. Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553
[79]. Kreis, A., Hirz, M., & Rossbacher, P. (2020). CAD-Automation in Automotive Development – Potentials, Limits and Challenges. *Computer-Aided Design and Applications*, *18*(4), 849-863. https://doi.org/10.14733/cadaps.2021.849-863
[80]. Kumar, V., & Viswanathan, S. (2023). Virtual Validation of Automotive Electronic Products for Climatic Test Conditions. *SAE Technical Paper Series*, *NA*(NA), NA-NA. https://doi.org/10.4271/2023-01-0157
[81]. Lamagna, M., Groppi, D., Nezhad, M. M., & Piras, G. (2021). A comprehensive review on Digital Twins for smart energy management system. *International Journal of Energy Production and Management*, 6(4), 323-334. https://doi.org/10.2495/eq-v6-n4-323-334
[82]. Lan, Y., Benomar, Y., Deepak, K., Aksoz, A., Baghdadi, M. E., Bostanci, E., & Hegazy, O. (2021). Switched Reluctance Motors and Drive Systems for Electric Vehicle Powertrains: State of the Art Analysis and Future Trends. *Energies*, *14*(8), 2079-NA. https://doi.org/10.3390/en14082079
[83]. Li, L., Ota, K., & Dong, M. (2017). When Weather Matters: IoT-Based Electrical Load Forecasting for Smart Grid. *IEEE Communications Magazine*, *55*(10), 46-51. https://doi.org/10.1109/mcom.2017.1700168
[84]. Li, M., Wang, J., Kumar, S., & Zheng, Y. (2022). Introduction to the Special Issue on Low Power Wide Area Networks. *ACM Transactions on Sensor Networks*, *18*(4), 1-2. https://doi.org/10.1145/3586058
[85]. Li, Q., Deng, Y., Liu, X., Sun, W., Li, W., Li, J., & Liu, Z. (2023). Autonomous Smart Grid Fault Detection. *IEEE Communications Standards Magazine*, *7*(2), 40-47. https://doi.org/10.1109/mcomstd.0001.2200019
[86]. Liu, T., & Hu, X. (2018). A Bi-Level Control for Energy Efficiency Improvement of a Hybrid Tracked Vehicle. *IEEE Transactions on Industrial Informatics*, *14*(4), 1616-1625. https://doi.org/10.1109/tii.2018.2797322
[87]. Liu, T., Tan, W., Tang, X., Zhang, J., Xing, Y., & Cao, D. (2021). Driving conditions-driven energy management strategies for hybrid electric vehicles: A review. *Renewable and Sustainable Energy Reviews*, *151*(NA), 111521-NA. https://doi.org/10.1016/j.rser.2021.111521
[88]. Liu, X., Ospina, J., & Konstantinou, C. (2020). Deep Reinforcement Learning for Cybersecurity Assessment of Wind Integrated Power Systems. *IEEE Access*, *8*(NA), 208378-208394. https://doi.org/10.1109/access.2020.3038769
[89]. Lopez, K. L., Gagné, C., & Gardner, M.-A. (2019). Demand-Side Management Using Deep Learning for Smart Charging of Electric Vehicles. *IEEE Transactions on Smart Grid*, *10*(3), 2683-2691. https://doi.org/10.1109/tsg.2018.2808247

[90]. Macher, G., Schmittner, C., Dobaj, J., Armengaud, E., & Messnarz, R. (2020). An Integrated View on Automotive SPICE, Functional Safety and Cyber-Security. *SAE Technical Paper Series*, *NA*(NA), NA-NA. https://doi.org/10.4271/2020-01-0145

[91]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40

[92]. Marcelino, C. G., Pérez-Aracil, J., Wanner, E. F., Jiménez-Fernández, S., Leite, G. M. C., & Salcedo-Sanz, S. (2023). Cross-entropy boosted CRO-SL for optimal power flow in smart grids. *Soft Computing*, *27*(10), 6549-6572. https://doi.org/10.1007/s00500-023-07900-y

[93]. Martyushev, N. V., Malozyomov, B. V., Khalikov, I. H., Kukartsev, V. A., Kukartsev, V. V., Tynchenko, V. S., Tynchenko, Y. A., & Qi, M. (2023). Review of Methods for Improving the Energy Efficiency of Electrified Ground Transport by Optimizing Battery Consumption. *Energies*, *16*(2), 729-729. https://doi.org/10.3390/en16020729

[94]. Md, A., Rokhshana, P., Mahiya Akter, S., & Anisur, R. (2025). AI-Powered Personalization In Digital Banking: A Review Of Customer Behavior Analytics And Engagement. *American Journal of Interdisciplinary Studies*, *6*(1), 40- 71. https://doi.org/10.63125/z9s39s47

[95]. Md Jakaria, T., Md, A., Zayadul, H., & Emdadul, H. (2025). Advances In High-Efficiency Solar Photovoltaic Materials: A Comprehensive Review Of Perovskite And Tandem Cell Technologies. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 201-225. https://doi.org/10.63125/5amnvb37

[96]. Md Mahfuj, H., Md Rabbi, K., Mohammad Samiul, I., Faria, J., & Md Jakaria, T. (2022). Hybrid Renewable Energy Systems: Integrating Solar, Wind, And Biomass for Enhanced Sustainability And Performance. *American Journal of Scholarly Research and Innovation*, *1*(1), 1-24. https://doi.org/10.63125/8052hp43

[97]. Md Majharul, I., Arafat Bin, F., & Ripan Kumar, P. (2022). AI-Based Smart Coating Degradation Detection For Offshore Structures. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 01-34. https://doi.org/10.63125/1mn6bm51

[98]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327

[99]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[100]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[101]. Md. Rafiqul Islam, R., Iva, M. J., Md Merajur, R., & Md Tanvir Hasan, S. (2024, 2024/01/25). Investigating Modern Slavery in the Post-Pandemic Textile and Apparel Supply Chain: An Exploratory Study. International Textile and Apparel Association Annual Conference Proceedings,

[102]. Meng, X., & Zhu, L. (2024). Augmenting cybersecurity in smart urban energy systems through IoT and blockchain technology within the Digital Twin framework. *Sustainable Cities and Society*, *106*(NA), 105336-105336. https://doi.org/10.1016/j.scs.2024.105336

[103]. Mohammad Shahadat Hossain, S., Md Shahadat, H., Saleh Mohammad, M., Adar, C., & Sharif Md Yousuf, B. (2024). Advancements In Smart and Energy-Efficient HVAC Systems: A Prisma-Based Systematic Review. *American Journal of Scholarly Research and Innovation*, *3*(01), 1-19. https://doi.org/10.63125/ts16bd22

[104]. Murgovski, N., Johannesson, L., Sjöberg, J., & Egardt, B. (2012). Component sizing of a plug-in hybrid electric powertrain via convex optimization. *Mechatronics*, *22*(1), 106-120. https://doi.org/10.1016/j.mechatronics.2011.12.001

[105]. Nassi, B., Mirsky, Y., Nassi, D., Ben-Netanel, R., Drokin, O., & Elovici, Y. (2020). CCS - Phantom of the ADAS: Securing Advanced Driver-Assistance Systems from Split-Second Phantom Attacks. *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, *NA*(NA), 293-308. https://doi.org/10.1145/3372297.3423359

[106]. Noor Alam, S., Golam Qibria, L., Md Shakawat, H., & Abdul Awal, M. (2023). A Systematic Review of ERP Implementation Strategies in The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02

[107]. Olivares-Rojas, J. C., Reyes-Archundia, E., Gutierrez-Gnecchi, J. A., Molina-Moreno, I., Cerda-Jacobo, J., & Mendez-Patino, A. (2022). Towards Cybersecurity of the Smart Grid Using Digital Twins. *IEEE Internet Computing*, *26*(3), 52-57. https://doi.org/10.1109/mic.2021.3063674

[108]. Opila, D. F., Wang, X., McGee, R. A., Gillespie, R. B., Cook, J. A., & Grizzle, J. W. (2012). An Energy Management Controller to Optimally Trade Off Fuel Economy and Drivability for Hybrid Vehicles. *IEEE Transactions on Control Systems Technology*, *20*(6), 1490-1505. https://doi.org/10.1109/tcst.2011.2168820

[109]. Palensky, P., Cvetkovic, M., Gusain, D., & Joseph, A. (2022). Digital twins and their use in future power systems. *Digital Twin*, *1*(NA), 4-4. https://doi.org/10.12688/digitaltwin.17435.2

[110]. Panda, D. K., & Das, S. (2021). Smart grid architecture model for control, optimization and data analytics of future power networks with more renewable energy. *Journal of Cleaner Production*, *301*(NA), 126877-NA. https://doi.org/10.1016/j.jclepro.2021.126877

[111]. Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence : Building blocks and an innovation typology. *Business Horizons*, *63*(2), 147-155. https://doi.org/10.1016/j.bushor.2019.10.004

Volume 04, Issue 01 (2025)
Page No: 175-201
eISSN: 3067-2163
Doi: 10.63125/xgp15k85

[112]. Perumal, V., Arul, T. G., Murugan, K., & Guruprasad, B. (2022). Energy management in a hybrid electric vehicle for the operating total cost minimization based machine learning. *AIP Conference Proceedings*, *2676*(NA), 50008-050008. https://doi.org/10.1063/5.0110119

[113]. Quintana, J. A. G., Alvarez, J. M., Verde, J. J., & Isasti, L. Z. (2021). NUEVA GENERACIÓN DE COMPONENTES MECÁNICOS Y ELECTRÓNICOS EN AUTOMOCIÓN: RETOS TECNOLÓGICOS PARA LOS SUMINISTRADORES. *DYNA*, *96*(6), 581-585. https://doi.org/10.6036/10145

[114]. Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital Twin: Values, Challenges and Enablers From a Modeling Perspective. *IEEE Access*, *8*(NA), 21980-22012. https://doi.org/10.1109/access.2020.2970143

[115]. Ripan Kumar, P., Md Majharul, I., & Arafat Bin, F. (2022). Integration Of Advanced NDT Techniques & Implementing QA/QC Programs In Enhancing Safety And Integrity In Oil & Gas Operations. *American Journal of Interdisciplinary Studies*, *3*(02), 01-35. https://doi.org/10.63125/9pzxgq74

[116]. Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42

[117]. Roksana, H., Ammar, B., Noor Alam, S., & Ishtiaque, A. (2024). Predictive Maintenance in Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30. https://doi.org/10.63125/hd2ac988

[118]. Sarker, M. T. H. (2025). Case Study Analysis of AI-Powered Sensor Fabrics for Continuous Health Monitoring in Chronic Disease Management. *Strategic Data Management and Innovation*, *2*(01), 160-180. https://doi.org/10.71292/sdmi.v2i01.18

[119]. Sarker, M. T. H., Ahmed, I., & Rahaman, M. A. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[120]. Sayghe, A., Hu, Y., Zografopoulos, I., Liu, X., Dutta, R. G., Jin, Y., & Konstantinou, C. (2020). Survey of machine learning methods for detecting false data injection attacks in power systems. *IET Smart Grid*, *3*(5), 581-595. https://doi.org/10.1049/iet-stg.2020.0015

[121]. Seetharaman, A., Patwa, N., Jadhav, V., Saravanan, A. S., & Sangeeth, D. (2020). Impact of Factors Influencing Cyber Threats on Autonomous Vehicles. *Applied Artificial Intelligence*, *35*(2), 105-132. https://doi.org/10.1080/08839514.2020.1799149

[122]. Shahan, A., Anisur, R., & Md, A. (2023). A Systematic Review Of AI And Machine Learning-Driven IT Support Systems: Enhancing Efficiency And Automation In Technical Service Management. *American Journal of Scholarly Research and Innovation*, *2*(02), 75-101. https://doi.org/10.63125/fd34sr03

[123]. Sharif, K. S., Uddin, M. M., & Abubakkar, M. (2024). NeuroSignal Precision: A Hierarchical Approach for Enhanced Insights in Parkinson's Disease Classification. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),

[124]. Sharma, N., & Habibullah, P. S. (2022). A Review of IoT Technology for the Connected Autonomous Vehicles Ecosystem. *Trends in Sciences*, *19*(7), 3072-3072. https://doi.org/10.48048/tis.2022.3072

[125]. Sher, F., Chen, S., Raza, A., Rasheed, T., Razmkhah, O., Rashid, T., Rafi-Ul-Shan, P. M., & Erten, B. (2021). Novel strategies to reduce engine emissions and improve energy efficiency in hybrid vehicles. *Cleaner Engineering and Technology*, *2*(NA), 100074-NA. https://doi.org/10.1016/j.clet.2021.100074

[126]. Shofiullah, S., Shamim, C. M. A. H., Islam, M. M., & Sumi, S. S. (2024). Comparative Analysis Of Cost And Benefits Between Renewable And Non-Renewable Energy Projects: Capitalizing Engineering Management For Strategic Optimization. *Academic Journal On Science, Technology, Engineering & Mathematics Education*, *4*(03), 103-112. https://doi.org/10.69593/ajsteme.v4i03.100

[127]. Siddiqui, N. A. (2025). Optimizing Business Decision-Making Through AI-Enhanced Business Intelligence Systems: A Systematic Review of Data-Driven Insights in Financial And Strategic Planning. *Strategic Data Management and Innovation*, *2*(1), 202-223. https://doi.org/10.71292/sdmi.v2i01.21

[128]. Siddiqui, N. A., Limon, G. Q., Hossain, M. S., & Mintoo, A. A. (2023). A Systematic Review Of ERP Implementation Strategies In The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02

[129]. Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. M. (2021). Digital Twin: Origin to Future. *Applied System Innovation*, *4*(2), 36-NA. https://doi.org/10.3390/asi4020036

[130]. Sini, J., Violante, M., & Dessi, R. (2020). ISO26262-Compliant Development of a High Dependable Automotive Powertrain Item. In (Vol. 1, pp. 315-326). Springer International Publishing. https://doi.org/10.1007/978-3-030-37161-6_23

[131]. Sohel, A., Alam, M. A., Hossain, A., Mahmud, S., & Akter, S. (2022). Artificial Intelligence In Predictive Analytics For Next-Generation Cancer Treatment: A Systematic Literature Review Of Healthcare Innovations In The USA. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 62-87. https://doi.org/10.62304/jieet.v1i01.229

[132]. Sohel, R. (2025). AI-Driven Fault Detection and Predictive Maintenance In Electrical Power Systems: A Systematic Review Of Data-Driven Approaches, Digital Twins, And Self-Healing Grids. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 258-289. https://doi.org/10.63125/4p25x993

[133]. Taşer, A., Kazanasmaz, T., Kundakcı Koyunbaba, B., & Durmuş Arsan, Z. (2023). Multi-objective evolutionary optimization of photovoltaic glass for thermal, daylight, and energy consideration. *Solar Energy*, *264*(NA), 112070-112070. https://doi.org/10.1016/j.solener.2023.112070

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Page No: 175-201
eISSN: 3067-2163
Doi: 10.63125/xgp15k85

[134]. Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering & System Safety*, *215*(NA), 107864-NA. https://doi.org/10.1016/j.ress.2021.107864
[135]. Tollner, D., Nyerges, Á., Jneid, M. S., Geleta, A., & Zöldy, M. (2024). How Do We Calibrate a Battery Electric Vehicle Model Based on Controller Area Network Bus Data? *Sensors (Basel, Switzerland)*, *24*(14), 4637-4637. https://doi.org/10.3390/s24144637
[136]. Tormos, B., Pla, B., Bares, P., & Pinto, D. (2022). Energy Management of Hybrid Electric Urban Bus by Off-Line Dynamic Programming Optimization and One-Step Look-Ahead Rollout. *Applied Sciences*, *12*(9), 4474-4474. https://doi.org/10.3390/app12094474
[137]. Tsiolakis, V., & Bensler, H. (2020). Current CAE Trends in the Automotive Industry. In (Vol. NA, pp. 169-179). Springer International Publishing. https://doi.org/10.1007/978-3-030-37752-6_10
[138]. Tsybunov, E., Shubenkova, K., Buyvol, P., & Mukhametdinov, E. (2018). Interactive (Intelligent) Integrated System for the Road Vehicles' Diagnostics. In (Vol. NA, pp. 195-204). Springer International Publishing. https://doi.org/10.1007/978-3-319-93710-6_21
[139]. Uddin Shipu, I., Bhowmick, D., & Lal Dey, N. (2024). Development and applications of flexible piezoelectric nanogenerators using BaTiO3, PDMS, and MWCNTs for energy harvesting and sensory integration in smart systems. *International Journal of Scientific and Research Publications*, *14*(6), 221. https://scholarworks.utrgv.edu/chem_fac/280/
[140]. Urooj, A., & Nasir, A. (2024). Review of intelligent energy management techniques for hybrid electric vehicles. *Journal of Energy Storage*, 92, 112132-112132. https://doi.org/10.1016/j.est.2024.112132
[141]. Wang, X., Ji, W., & Gao, Y. (2023). Energy Consumption Optimization Strategy of Hybrid Vehicle Based on NSGA-II Genetic Algorithm. *Processes*, *11*(6), 1735-1735. https://doi.org/10.3390/pr11061735
[142]. Wang, Y., & Jiao, X. (2022). Dual Heuristic Dynamic Programming Based Energy Management Control for Hybrid Electric Vehicles. *Energies*, *15*(9), 3235-3235. https://doi.org/10.3390/en15093235
[143]. Wang, Y., Kang, X., & Chen, Z. (2022). A survey of Digital Twin techniques in smart manufacturing and management of energy applications. *Green Energy and Intelligent Transportation*, *1*(2), 100014-100014. https://doi.org/10.1016/j.geits.2022.100014
[144]. Xie, G., Yang, K., Xu, C., Li, R., & Hu, S. (2022). Digital Twinning Based Adaptive Development Environment for Automotive Cyber-Physical Systems. *IEEE Transactions on Industrial Informatics*, *18*(2), 1387-1396. https://doi.org/10.1109/tii.2021.3064364
[145]. Yadlapalli, R. T., Kotapati, A., Kandipati, R., & Koritala, C. S. (2022). A review on energy efficient technologies for electric vehicle applications. *Journal of Energy Storage*, *50*(NA), 104212-104212. https://doi.org/10.1016/j.est.2022.104212
[146]. Yapeng, L., Tang, X., Lin, X., Grzesiak, L. M., & Hu, X. (2022). The role and application of convex modeling and optimization in electrified vehicles. *Renewable and Sustainable Energy Reviews*, *153*(NA), 111796-NA. https://doi.org/10.1016/j.rser.2021.111796
[147]. Yu, W., Patros, P., Young, B., Klinac, E., & Walmsley, T. G. (2022). Energy digital twin technology for industrial energy management: Classification, challenges and future. *Renewable and Sustainable Energy Reviews*, *161*(NA), 112407-112407. https://doi.org/10.1016/j.rser.2022.112407
[148]. Zhang, Y., Huang, T., & Bompard, E. F. (2018). Big data analytics in smart grids: a review. *Energy Informatics*, *1*(1), 1-24. https://doi.org/10.1186/s42162-018-0007-5
[149]. Zhang, Z., Zou, Y., Zhou, T., Zhang, X., & Xu, Z. (2021). Energy Consumption Prediction of Electric Vehicles Based on Digital Twin Technology. *World Electric Vehicle Journal*, *12*(4), 160-NA. https://doi.org/10.3390/wevj12040160
[150]. Zhao, K., He, K., Liang, Z., & Mai, M. (2023). Global Optimization-Based Energy Management Strategy for Series–Parallel Hybrid Electric Vehicles Using Multi-objective Optimization Algorithm. *Automotive Innovation*, *6*(3), 492-507. https://doi.org/10.1007/s42154-023-00225-4
[151]. Zou, W.-Q., Pan, Q.-K., Meng, T., Gao, L., & Wang, Y.-L. (2020). An effective discrete artificial bee colony algorithm for multi-AGVs dispatching problem in a matrix manufacturing workshop. *Expert Systems with Applications*, *161*(NA), 113675-NA. https://doi.org/10.1016/j.eswa.2020.113675
[152]. Zou, Y., Liu, T., Liu, D., & Sun, F. (2016). Reinforcement learning-based real-time energy management for a hybrid tracked vehicle. *Applied Energy*, *171*(NA), 372-382. https://doi.org/10.1016/j.apenergy.2016.03.082